LEVELS AND DETERMINANTS OF HOSPITAL INEFFICIENCY

by

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FORWARD

This was a collaborative project, but the division of labor was not split equally. Sear assumed responsibility for running the DEA model. Chirikos assumed responsibility for data editing and variable construction, the estimation of the frontier regression model, and the analysis of efficiency correlates and concordance; he also drafted most of this *Report*.

With the usual disclaimers, both investigators wish to acknowledge the important contributions of the following individuals in conducting this project:

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EXECUTIVE SUMMARY

Despite sustained public policy efforts over the past two decades to induce hospital managers to use their resources more efficiently, it is unclear whether hospitals are now actually less inefficient than they once were or whether further efficiency gains can be expected in future years. The principal objectives of this research project are to apply two relatively new methods to quantify inefficiency levels in the hospital industry and to compare the results yielded by each method. In particular, the potential for using Data Envelopment Analysis (DEA) and frontier regression (FREG) techniques to construct inefficiency scales for acute care hospitals is examined. These methods permit inefficiencies to be conceptualized as deviations from *best-practice* input/output relationships, rather than the *average* of such relationships. A longitudinal data set on service production and costs in 186 acute care Florida hospitals in continuous operation over the period 1982-1993 is assembled to carry out this task. Longitudinal data permit some degree of control over unobservable management factors likely to influence measured inefficiency.

The analysis first constructs a common set of input and output indicators, specifies comparable data envelopment and frontier regression models, and estimates these models to obtain the efficiency values or scores yielded by each. The empirical results are then examined in some detail in order to assess the degree to which these models produce convergent or divergent evidence about hospital efficiency. Multivariate statistical analyses of the main correlates or determinants of measured efficiency are carried out. These findings are employed to appraise some aspects of the construct validity of the data envelopment and frontier regression efficiency scores, to account for the factors contributing to divergence in these scores, and to draw inferences about public policies that might improve the efficiency of hospital service delivery.

The principal findings from the study are:

- A significant and unchanging level of inefficiency is detected in the way the panel of study hospitals utilize resources. Despite slight variations by model and time point, overall inefficiency residuals are estimated to be on the general order of 14 percent of the *best-practice* efficiency level identified by each method. This implies that inefficiency continues to exact a high economic toll; it also implies that hospital cost containment efforts still have much to accomplish. The analysis also suggests that the absence of substantial efficiency improvements over time stems, in part, from the persistence of hospital behavior known to raise input/output ratios and lower market specialization rates. Evidence is adduced, for example, that hospitals still engage in non-price competition for physicians and their patients, in spite of market and policy developments aimed at curbing the use of these cost-augmenting strategies.

- The efficiency scores derived from the data envelopment and frontier regression analyses correlat fairly well at the level of the industry, but not nearly as well at the level of individual hospital observations. Put somewhat differently, each portrays the attributes or characteristics of the most "efficient" hospital in significantly different terms. We infer from this that the two methods tap somewhat different dimensions (or different types of) efficiency. We also infer that the differences in the efficiency scoring of the two methods are not simply attributable to the chance factors that are encompassed by the frontier regression method and omitted in the data envelopment model.

Although these findings are based on data referring to a single state, we believe they are generalizable to the rest of the nation. We also judge them to be encouraging enough to warrant more intensive research efforts in the future. Of several key priorities, the need to conduct comparative analyses of data envelopment and frontier regression methods along the lines pursued here with other data sets stands out. In the absence of such additional research, the identification of "efficient" hospitals for purposes of reimbursement and cost containment policies will remain illusive and heavily dependent on the choice of methodological approach.

INTRODUCTION

Despite sustained public policy efforts over the past two decades to induce hospital managers to use their resources more efficiently, it is unclear whether hospitals are now actually less inefficient than they once were or whether further efficiency gains can be expected in future years. The principal objectives of this research project are to apply two relatively new methods to quantify inefficiency levels in the hospital industry and to compare the results yielded by each method. In particular, the potential for using Data Envelopment Analysis (DEA) and frontier regression (FREG) techniques to construct inefficiency scales for the acute care hospital sector is examined. A longitudinal data set on acute care hospital costs and production in the state of Florida over the period 1982-1993 is assembled to carry out this task.

The analysis first constructs a common set of input and output indicators, specifies comparable DEA and FREG models, and estimates these models to obtain the efficiency values or scores yielded by each. The DEA and FREG results are then examined in some detail in order to assess the degree to which these models produce convergent or divergent evidence about hospital efficiency. Multivariate analyses of the main correlates or determinants of measured efficiency are carried out. These findings are employed to appraise some aspects of the validity of the DEA and FREG efficiency scores, to account for the factors contributing to divergence in these scores, and to draw inferences about public policies that might improve the efficiency of hospital production.

The analysis gauges hospital inefficiency in both more appropriate and detailed fashion than many past studies of hospital production and costs. For one thing, the DEA and FREG methods permit inefficiencies to be conceptualized as deviations from *best-practice* input/output relationships, rather than the *average* of such relationships. For another, the longitudinal data set permits some degree of control over unobservable management factors likely to influence measured inefficiency. For yet another, consistently specified DEA and frontier regression models estimated on the same data set provide a meaningful comparison of the two approaches, something not yet attempted in the policy-relevant literature on hospital services. Even though the analysis uses data from only one state, the substantive and methodological inferences drawn from the analysis are generalizable and, in our judgment, contribute to that literature.

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DISCUSSION
Hospital Efficiency as a Research Priority

Although the rising cost of hospital care has slowed somewhat since the implementation of the Medicare Prospective Payment System (PPS), prices and real expenditures in the hospital sector continue to increase at rates well above those observed elsewhere in the national economy (Levit et al., 1994). Even though annual rates of increase in hospital prices measured by the HCFA Hospital Input Price Index and the hospital component of the BLS Consumer Price Index were both roughly 2.7 percentage points lower in the decade after PPS was implemented than in the decade prior to its implementation, they nonetheless continue to be several percentage points higher than the annual rates of increase in the GDP deflator or CPI All Items (less Medical Care) since 1983. Real hospital expenditures increased in the decade since PPS at annual rates that are 2.0-2.3 percentage points lower than the rates observed during the 1970s, but still at a pace that is roughly double the rate needed to keep per capita expenditures constant; consequently, intensity of service or the resource cost of a case has continued to increase at least by 1.5 percent per year in recent years (Ashby and Lisk, 1992; Christensen, 1991). In the absence of more extensive and effective cost containment efforts, many specialists believe that these trends will continue (King, 1994; Waldo et al., 1992).

Explanations of the continuing rise in the costs of hospital care are typically predicated on the assumption that there is insufficient economic discipline in this sector to ensure that hospital managements (broadly defined here to include both administrators and governance boards) use resources and introduce new technology judiciously. In contrast to other industries, the discipline imposed by the external market place in the hospital industry is weakened by the widespread availability of health insurance. Managers, as a result, produce a broader range and higher level of hospital services than is efficient from a purely economic perspective. Furthermore, the potential discipline of the internal administrative structure and authority lines of many hospitals may be weakened by the methods used to reimburse hospitals--particularly the long-standing use of retrospective, cost-based reimbursement methods. Managers, therefore, hire more, and more costly, human and capital resources (per unit of output) than is efficient from a purely technical perspective. In the language of the current literature, factors such as insurance availability and reimbursement policy subject the production of hospital services to both allocative and technical inefficiencies (Frantz, 1992).

There are reasons to suppose that such inefficiencies have not yet been entirely squeezed out of the hospital sector by current cost containment efforts. For one thing, the figures on cost trends summarized above suggest that inflationary forces are still at work. For another, there are as yet no obvious signs that key types of hospital behavior have changed. For instance, there is very little hard evidence that hospitals yet compete routinely on the basis of price and, in fact, there is recent evidence suggesting that they continue to rely on non-

price competitive strategies in the local market to attract physicians and their patients (Chirikos, 1992; Dranove et al., 1992 ,1993; and Melnick et al., 1992). Similarly, there is little hard evidence that the structure and processes of internal decision making in hospitals have changed in ways that would make managers more cost conscious. To be sure, there is anecdotal evidence that hospitals are now operated in a more "business-like" manner, and that managers have tightened budget control functions and the like (Coulam and Gaumer 1991). However, more fundamental changes in the structure and functioning of decision mechanisms bearing on the use of scarce resources, if they have actually occurred, have not yet been fully documented.

Clearly, additional research is called for to investigate the extent to which hospital behaviors of this sort continue to pose a significant problem warranting public policy action. At the strategic level, the design of health care cost containment policy hinges on a fuller appreciation of how deeply-rooted inefficient behavior is in the institutional arrangements and "culture" of hospital administration. At the tactical level, these behavior patterns are important in judging the potential effectiveness of various reimbursement strategies. A case in point is the continuing controversy in both policy and academic circles about the desirability of "blending" PPS rates with the cost experience of individual hospitals as a means of inducing more efficient resource utilization (Coulam and Gaumer, 1991; Pope, 1990)

More fundamental perhaps is the need for this research effort to be firmly anchored to meaningful data on actual levels and trends in hospital inefficiency. Remarkably, we still know very little about these matters. Until quite recently, the knowledge base was limited to indirect inferences drawn from the econometric literature of the 1970s and 1980s on hospital cost/production functions (Cowing et al., 1983; Hadley and Zuckerman, 1991). This literature provides an inadequate base for current policy purposes, however, in part because it is heavily based on pre-PPS cross-sectional data, and in part because it typically used ordinary regression methods capable of estimating only the *average* cost or production function as opposed to the *best-practice* function. New methods are now available that permit inefficiency to be indexed as deviations from best practice, and a small number of studies applying these methods to health service delivery have already been published.[1] Clearly, additional studies using these new methods are needed to augment the stock of policy-relevant knowledge about efficiency relationships in the hospital industry.

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[1] See, among others, Banker, et al., 1986; Bitran, and Valor-Sabaiter, 1987; Borden, 1988; Chiligerian and Sherman, 1990; Dor, 1994, Grosskophf and Valdmanis, 1987 and 1993; Huang, 1989 and 1990; Morey et al., 1990 and 1992; Nunnamaker, 1983; Ozcan et al, 1992 and 1993; Register and Bruning, 1987; Sexton et al., 1989; Sherman, 1986; Vitaliano and Toren, 1994; Wagstaff, 1989; Zuckerman, Hadley and Iezzoni, 1994).

This next generation of studies should focus immediately on at least three primary gaps in the incipient literature. First, different types of frontier models need to be tested and subjected to cross-validity checks. If different frontier methodologies purport to measure the same underlying phenomenon, then studies should be conducted to assess the concordance of their findings. Second, not unlike the previous generation of cost/production function studies, most of the early frontier studies are also constrained by either cross-sectional data and/or relatively aggregate measures of inputs and outputs (Newhouse, 1994). For example, in what surely must be regarded as the best frontier regression analysis of hospital costs done to date, Zuckerman et al. (1994) rely solely on a 1987 cross-sectional data set. Furthermore, despite an extremely rich set of measures of health conditions and diagnoses, these researchers model only five output and two factor price variables. Finally, given the ability of frontier methods to measure inefficiency in direct fashion, studies need to pay closer attention to covariates, i.e., the factors responsible for pushing efficiency levels higher or lower. For understandable reasons, early studies have concentrated heavily on just the estimation of the efficiency value itself. Clearly, new studies using frontier-related techniques that attempt to overcome limitations of this sort should be accorded high priorities on the research agenda.

Research Objectives and Organization of Report

Given the foregoing, the research reported here is designed to achieve the following major aims:

First, to measure hospital efficiency by means of alternative methods and in ways that permit the results yielded by each method to be compared. We draw on Data Envelopment Analysis (DEA) and frontier regression (FREG) techniques to index the degree to which hospitals use resources efficiently. We assemble a single longitudinal data set on hospital costs and production, construct a common set of input and output indicators, specify comparable DEA and FREG models, and estimate these models to obtain the efficiency values (scores) yielded by each. We then compare the DEA and FREG results to assess the degree to which these models produce convergent or divergent evidence about hospital efficiency.

Second, to investigate the main correlates or determinants of measured efficiency, and to use these finding to appraise the construct validity of the DEA and FREG efficiency scores, to account for the factors contributing to divergence in these scores, and to draw inferences about public policies that might improve the efficiency of future hospital production. We specify multivariate regression models designed to measure the net effects, if any, of various factors internal and external to the hospital typically expected to influence the efficiency level of the facility. We test these models directly with the efficiency scores yielded by the estimation of the DEA and FREG models. We also test variants of these models to account for the degree of concordance between the DEA and FREG results.

Finally, to draw from the analysis both substantive and methodological implications for public policy. The study is designed to add to the substantive knowledge base about how, and how well, hospitals deliver services. Methodologically, the study is the first to estimate DEA and FREG models of hospital efficiency directly and in fully comparable fashion. It appraises the relative merits of these state-of-the-art techniques and provides some criteria for choosing between them.

The *Report* is organized as follows. The next section provides a conceptual overview of the technical tasks and assumptions required to carry out the study. The third section then describes in some detail the Florida data set assembled for purposes of this study. We show that the longitudinal record of Florida hospitals over the period 1982-1993 is not only important in its own right, but that it generalizes reasonably well to the entire U.S. hospital industry.

The fourth section sets out the methods and empirical findings of the analysis of efficiency levels and changes in Florida hospitals over time. This section considers, in turn, the construction of the input and output variables, the specification of the DEA and FREG models, the partitioning of the sample data, descriptive data, and the analytic results derived from estimating the DEA and FREG models. Among other things, we find that significant inefficiency is still in evidence in the sample data, and that the overall level of efficiency has not changed much over the past 12 years. We also find that, while the DEA and FREG efficiency scores correlate reasonably well at the level of the industry, they differ greatly at the level of individual observations. This implies that conclusions about inefficiency differ somewhat depending upon whether one chooses to rely on either the DEA or FREG evidence.

Accordingly, the fifth section sets out the methods and empirical results of a detailed analysis of efficiency correlates and concordance. A set of predictor variables characterizing the internal and external environmental influences on efficiency-related decision processes is constructed. Various multivariate models are then estimated to assess how much of the variance in measured efficiency can be explained by the set of predictors. We find, among other things, that DEA and FREG results diverge systematically with respect to the size and control status (ownership) of the facility.

The final section of the *Report* sets out the policy-related conclusions of the analysis, and suggests some of the next steps needed to investigate hospital efficiency questions in the future.

Methods

Conceptual Framework: An Overview

The following analysis is predicated on the relatively straightforward proposition that hospital production and the demand for inputs that it generates is influenced by the way hospital management responds to a broad set of external and internal conditions (Lee, 1971; Newhouse,

1970). Externally, the dynamics of local health care competition, regulatory efforts, and technological diffusion shape managerial decisions about the quantity and quality of services delivered by the hospital, controlling for the distribution of health problems (case mix) and the socioeconomic factors shaping the demand for hospital services aggregated over the local market at a point in time. Internally, the dynamics of institutional organization, medical staff arrangements, and practice patterns shape managerial decisions about the quantity and quality of factor inputs needed to produce the requisite services, controlling for case mix and economic demand aggregated over the divisions of the facility at a point in time (Alexander and Morrisey, 1988; Feinglass, et al., 1991; Pauley, 1978).

This would not be altogether noteworthy if managerial decision making was subject to consistent and sequentially applied criteria in the sense that the external market dictated the level and mix of output and the internal market dictated the derived demand for factor inputs. However, that is usually not the case. Qualitative dimensions of hospital production are reflected in factor intensities and may be varied in response to external market or inter-institutional rivalries, while the quality or reputation of the hospital staff (medical and managerial alike) is reflected in the level and mix of delivered services and may be varied in response to internal market or intra-institutional rivalries. Decisions of what to produce and how best to produce it, in other words, must in the case of the hospital typically meet both external and internal market "tests," cf., Harris (1977). Since these tests need not be, and indeed often are not, consistent, inefficiency results. We believe that tension between external and internal decision processes has over time driven input/output ratios upwards and market specialization ratios downwards, and thereby has been a major contributor to the historical rise in the costs of hospital care. Although PPS and other cost containment tools have attempted to drive a wedge between these decision processes, it is not yet clear that they have done so successfully enough to have squeezed all inefficiencies out of the production of hospital services. The question of how much inefficiency remains lies at the heart of the analysis reported herein.

In order to investigate this topic, it is necessary to measure the level and distribution of hospital inefficiency over time. The task of measuring hospital inefficiency has always been problematic because of the difficulties associated with measuring output correctly and incorporating the multiple outputs of hospital productive activity in statistical models (Cowing, et al., 1983; Carey and Stefos, 1992). We use Data Envelopment Analysis (DEA) and frontier (FREG) cost functions to gauge relative inefficiency levels across hospitals at multiple points in time. Both types of methods are deployed in this study to gauge inefficiency for two main reasons.

One is that each is a comparatively recent methodological development touted in the literature as a significant improvement in the state-of-the-art (Banker et al., 1988; Zuckerman et al., 1994). There have

not yet been, however, systematic studies in the health care field comparing the results of the two methods. As a result, health policy makers interested in efficiency issues have little basis for deciding whether to use either or both of these new models (Batavia et al., 1994). The results of the present study should contribute useful information to those faced with making such decisions.

The other reason is that efficiency in general, and hospital efficiency in particular, are slippery concepts, so the more ways that can be found to gauge them, the better. In principle, the results of using either model should point to the same institutions at various points in time as comparatively more or less efficient than others. Our study is predicated on this principle. In practice, of course, DEA and FREG results may differ for several reasons, not the least of which is the way each treats random or chance factors bearing on input-output relationships. As will be described in more detail below, DEA is a deterministic (non-parametric) approach that makes no allowance for chance factors in separating the efficient from the inefficient. In contrast, FREG is a stochastic (parametric) technique that deliberately models deviations from the frontier cost/output level in terms of a composable error comprised of both statistical "noise" and systematic efficiency differences. *A priori*, it is unclear whether the nonparametric/parametric forms of the two models should produce large differences in measured efficiency. A comparative analysis should prove useful in narrowing the degree of uncertainty about this question and thereby contribute to the appropriate utilization of either or both models.

In part because of our interest in comparing the results of DEA and FREG efficiency estimates, we deliberately limit their specification in the first stage of the analysis to relevant vectors of inputs and outputs, leaving covariates or explanatory variables to be introduced in a second-stage analysis of correlates and concordance. The decision to pursue the analysis in two stages is explained principally by different limitations in each method. DEA models, for instance, can only use continuously measured variables and are highly susceptible to outlier values on those continuous scales. Many important predictor variables of high or low efficiency levels, however, are measured categorically (e.g., ownership), so they cannot be incorporated into the DEA estimation. While such covariates can easily be incorporated directly into the FREG specification, including them in only one model violates a necessary condition for a systematic comparison of the two methods. Moreover, the two-stage approach also facilitates FREG estimation by reducing the burden of extremely large numbers of regressors typically encountered in translog specifications of the cost function. Limiting the first stage of the analysis to the measurement of the efficiency dimensions of observed input/output relationships is thus a key aspect of our conceptual framework.

After the DEA and FREG models are estimated and compared, the analysis turns to the consideration of the factors that tend to increase or decrease efficiency scores. Explanatory models are formulated to test the extent to which observed characteristics of the internal and

external environments of hospital managers account for variations in measured efficiency (Eakin, 1991; Register and Bruning, 1987). These models turn out to play both substantive and methodological roles in this research. Substantively, the correlates of efficiency scores provide important clues about the potential effectiveness of policy interventions designed to make hospitals use their resources more wisely. Indeed, some policy makers may fail to appreciate the importance of measuring efficiency levels or trends in the absence of concrete evidence about the factors responsible for shaping those values. Methodologically, the explanatory models provide a validity check on the results of the DEA and FREG analyses and, thereby, a means of appraising the sometimes conflicting evidence adduced by each method.

Florida Data Set

A significant amount of the time needed to conduct this project went into assembling, editing, and refining a longitudinal data set on Florida short-term general hospitals. This newly constituted data set has some advantages over other available ones. The information is generally more detailed. It is also longitudinal in design, so it can be used to trace efficiency changes over time, while simultaneously controlling for unmeasured or unobservable factors bearing on efficiency-related decisions at the level of individual hospitals. The data set is comprised of two main parts. The largest of these was created by merging public use computer tapes from the Florida Health Care Cost Containment Board (HCCB), or what is now known as the Florida Agency for Health Care Administration (AHCA), (hereafter referred to as HCCB/ACHA) on financial reports submitted each year by hospitals operating in the state. Subsequent subsections describe the preparation and editing of these financial reports, the selection of a longitudinal subsample of hospitals for use in the statistical analysis, a brief appraisal of the degree to which this panel or longitudinal sample generalizes to the state and nation, and a complementary data set on the characteristics of the local health care markets in which these hospitals operate.

Hospital Financial Reports

Florida has required since 1979 that each hospital in the state submit various reports about financial performance on an annual basis to HCCB/ACHA. Much of this information is legally mandated by the prospective budgetary review process conducted by HCCB/ACHA since 1980 and, as a result, the data are currently available in public use form for each year since that review process was initiated. Data collected between 1979 and 1981, however, were quite sketchy, so for operational purposes, detailed data are available only since 1982. At the time this project started, the most recent year for which the public use tapes were available was 1993. Consequently, the data set covers the period 1982-1993, inclusive.

The data submitted each year minimally include service output indicators, inputs, operating expenses and revenues. These data are fairly detailed and, because they are legislatively mandated, reasonably

complete. Nonetheless, gaps remain. For one thing, the public use tapes strip proprietary information on the discount pricing practices of hospitals. For another, the financial reports contain little information on case mix. Patient-level discharge records in a UB82 format have been available from HCCB/AHCA since late 1987, and they can now be linked via a hospital identification number to the financial report. However, with the exception of the patient-origin data used in delineating local hospital markets (described below) this study makes no use of these discharge records. We chose deliberately instead to concentrate on the financial reports available for the longer historical period 1982-1993 because this longer period better serves our immediate research aims.[2] Incorporating diagnostic data in more detailed efficiency models for the period 1988-onwards is left for future work.

The decision to delimit the data set along these lines was also influenced by the lengthy process needed to assemble, organize, extract, disaggregate, and perform preliminary edits on the financial reports for each year over the period 1982-1993. These interrelated tasks took substantially more time to accomplish than originally planned for two reasons. One was that difficulties were encountered in reading the data tapes for a few years as a result of changes in tape formats and in the conventions used by different programming staffs of the (then) HCCB. The other was that it proved difficult to trace specific data items over time in unambiguous fashion. It should be noted here that the data submitted to the HCCB/ACHA are actually entered into "account files" corresponding to each question or request display on the form that the hospital fills out each year. The practical implication of this is that the financial reports for the study period 1982-1993 are actually comprised of more than 845,000 account files. These reports needed to be transposed and aggregated to the level of individual hospitals. We also discovered that because some hospitals did not always file their financial reports on time, and because some others changed ownership and each owner filed a partial report that was left unconsolidated on the data tape, many account files referred only to part of a year or occasionally to another fiscal year than the one for which the primary report was filed. This meant that a number of specific account files needed to be tracked down and then "spliced" or otherwise combined to represent the activities of the institution for a given year.

Additional editing was then frequently required to fill gaps in the consolidated account files. Because missing data are difficult to deal with in DEA estimation and the use of panel regression methods, we imputed missing values for some variables in reference to temporally adjacent values for a given hospital. We also discovered that a much larger fraction of highly detailed data items was fragmented than originally supposed. Many key items such as detailed cost figures for

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[2] Concern about the consequences of this decision eased somewhat when Zuckerman et al. (1994) reported that an extensive vector of health outcome and quality variables contributed little to the results of their frontier regression analysis of hospital costs.

sub-units or categories of cost centers of the institution needed to be adjusted to control totals or sub-totals. Cleaning up the data set was a tedious and time-consuming task.

Selecting Panel Hospitals, 1982-1993

We restrict the analysis to short-term, acute care hospitals in the HCCB/ACHA financial data set. We believe that including long-term facilities or even short-term specialty hospitals would confound the results of the efficiency analysis. Delineating the set of short-term, acute care hospitals for purposes of the analysis proved to be more complicated, though also more interesting from a substantive view, than initially supposed. The reason is that the Florida hospital industry experienced considerable churning between 1982 and 1993, not only with respect to the number of facilities closing or opening at various points in time or the number acquired or divested by investor groups, but also the number that shift the type of care they provide in response to changes in reimbursement strategy or patient populations. In this latter category are facilities that moved from short-term to long-term patient care or back again (in a few cases, more than once in either direction) over the period in question; some other facilities moved from specialty care to general care, and back again. We winnowed the list of short-term general (acute care) hospitals by various means, including telephone interviews with executive officers of a number of facilities around the state to confirm the historical evolution of their control, ownership, and patient care populations.

This work identified a set of 186 institutions that were in continuous operation over the entire study period; it also identified a set of roughly 54 facilities which met the criteria of short-term acute care facilities, but whose longitudinal records are either left-censored (i.e., new facilities that opened after 1982) or right-censored (i.e., facilities that went out of business before 1993). The present study is restricted to the set of 186 institutions in continuous operation over the study period. When the annual data on these institutions are pooled for the 12-year period, we have an effective sample of 2,232 hospitals (or hospital-years); we refer to this sample throughout as "all panel hospitals."

Table 1 shows some selected characteristics of the panel hospitals relative to the set of censored facilities with fewer than 12-years of experience over the study period. As can be seen, there are some differences in both the distribution of these two sets of hospitals by control status and by bed size. Not surprisingly, proprietary hospitals are somewhat more likely to come in, or go out of, business as are small and medium-size facilities. A preliminary survivor analysis using a parametric waiting time model (not reported here) confirms that these differences are significant and more likely to occur in highly competitive local health care markets. Yet, we do not believe that omitting the censored set imparts much bias to the statistical analyses reported below. It is, in any case, outweighed by the advantage of using a balanced panel data set in both stages of the statistical analysis.

Table 1
Selected Characteristics, Panel and Censored
Sets of Hospitals, Florida, 1982-1993[a]

Selected Characteristics[b]	Hospital Sets	
	Panel	Censored
Hospital Control		
Number	2,232	283
Percent	100.0	100.0
Religious	7.4	0.4
Community	34.7	25.8
Proprietary Corporation	37.6	49.5
Other Proprietary	3.4	3.2
Government	16.8	21.2
Bed Size (Licensed Beds)		
Mean Number	281.8	142.4
Percent	100.0	100.0
Small (100 or Fewer)	20.7	31.8
Medium (101-299)	44.4	62.5
Larger (300 or More)	34.9	5.7

a. See text for a description of the panel and censored groupings of Florida short-term general hospitals.

b. See Appendix Table A.1 for variable descriptions.

Note: Percentages may not add up due to rounding.

Panel Comparisons With Florida and the U.S.

These comparisons were created in order to put the panel of hospitals studied here into perspective with other short-term Florida and U.S. hospitals. It should be noted at the beginning of this analysis that the data available from the American Hospital Association for U.S. hospitals constituted a slightly different group than the Florida and panel hospitals. AHA data were only available for "community hospitals," which include some sub-acute services which were excluded from the panel of hospitals studied here. This artifact, undoubtedly, slightly affects the comparisons between these U.S. hospitals and the panel hospitals.

Figure 1 shows the average length of stay per inpatient hospital admission. The panel hospitals had a consistently shorter length of stay than either the Florida or U.S. hospitals, which is to be expected given the exclusion of sub-acute cases from the panel hospitals. Despite the artifact, Florida hospitals, undoubtedly, have a shorter length of stay than U.S. hospitals because of the relatively high proportion of for-profit hospitals in Florida (see Figure 6 below). The ALOS declined for panel hospitals from 7.2 days in 1982 to six days in 1993, while for U.S. hospitals, ALOS declined from 7.6 days in 1982 to 7.0 days in 1993. Thus, the percent decline in average length of stay from 1982 through 1993 was twice as large for panel hospitals as it was for U.S. hospitals (a decline of 17 percent versus 8 percent).

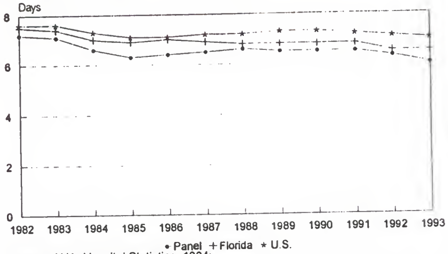
The differences in occupancy rates for the three groups of hospitals are shown in Figure 2. The panel hospitals had significantly lower occupancy rates than U.S. hospitals in all years, with the gap widening over time. Panel hospital occupancy rates declined from 68.3 per cent in 1982 to 49.1 percent in 1993 (a decline of 28 percent), while U.S. community hospital occupancy rates dropped from 75.3 percent in 1982 to 64 percent in 1993 (a decline of 15 percent).

Figure 3 shows that the panel (and Florida hospitals) had significantly more beds per hospital than did U.S. community hospitals. Given the relatively higher level of urbanization in Florida compared to the U.S., in general, it is not surprising that mean bed size is higher in Florida. Mean number of beds in panel hospitals rose from 265 in 1982 to 293 in 1993 (an increase of about 11 percent), while mean number of beds for U.S. hospitals barely changed over this same period of time (from 173 to 175). The change for the panel is probably, in part, an artifact of the methodology used to construct the panel, with the larger hospitals being the "survivors", and the smaller hospitals being the ones which closed, and were, therefore, excluded.

Figure 4 contains a comparison of the cost per day of hospitalization and shows a very interesting pattern over time. From 1982 through 1987 the cost per day of hospitalization was barely indistinguishable among the three groups of hospitals. In 1987 the cost per day for Florida (and panel) hospitals began to increase at a higher rate than U.S. hospitals, resulting in a difference in 1993 of $84.59 per day.

Figure 1

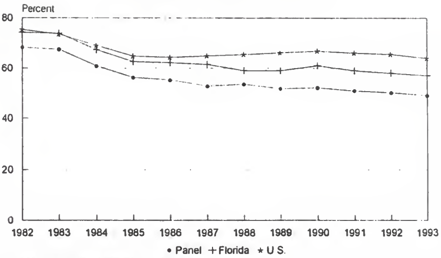
Average Length of Stay Per Inpatient Hospital Admission



Source: AHA, Hospital Statistics, 1994;
FHA, Environmental Assessment, 1994.

Figure 2

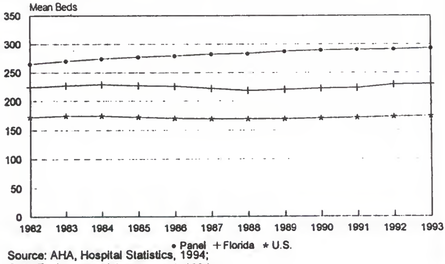
Hospital Occupancy Rates



Source: AHA, Hospital Statistics, 1994;
FHA, Environmental Assessment, 1994.

Figure 3

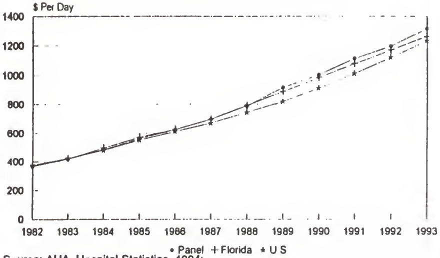
Average Number of Beds Per Hospital



Source: AHA, Hospital Statistics, 1994;
FHA, Environmental Assessment, 1994.

Figure 4

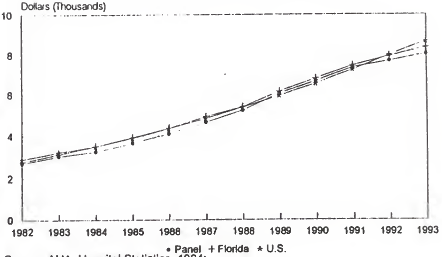
Cost Per Day of Hospitalization



Source: AHA, Hospital Statistics, 1994;
FHA, Environmental Assessment, 1994.

Figure 5

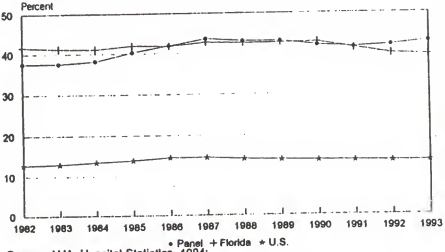
Cost Per Inpatient Hospital Stay



Source: AHA, Hospital Statistics, 1994;
FHA, Environmental Assessment, 1994.

Figure 6

Percent of Hospitals Investor-Owned



Source: AHA, Hospital Statistics, 1994;
FHA, Environmental Assessment, 1994.

Thus, cost per day accelerated at a higher rate in panel hospitals from 1988-1993 than it did in U.S. hospitals. Thi becomes even more interesting when put into the context of Figure 5 wnich shows the total cost per inpatient stay. This Figure shows that there were very small differences between the panel, Florida and U.S. hospitals from 1982-1991 on this variable. Then, in 1992 the cost per stay in Florida and U.S. hospitals began to increase at a higher rate than panel hospitals, resulting in a difference of $300.00 between panel and U.S. hospitals in 1993. Thus, the panel hospitals in 1993 had a higher cost per day than U.S. hospitals, but a lower cost per stay, because of the significantly lower average length of stay in panel hospitals.

Finally, Figure 6 shows that the U.S. has continuously had a lower percentage of investor-owned hospitals than has Florida or the panel. Investor-owned hospitals have consistently represented about 13-14 percent of all U.S. community hospitals, while in Florida (and the panel) this percentage has been around 38-42. To the extent that one must be cautious about generalizing results from studies of Florida hospitals to the nation, the difference in percent investor-owned, and variables which are closely correlated with this, differentiate Florida from the nation. Florida more closely resembles other more populous sunbelt states, e.g., Texas and California, than it does the rest of the U.S. on this variable.

Market Data

In addition to the financial reports of the panel sample of Florida hospitals, we pieced together an auxiliary data set characterizing the external environment in which these hospitals operate. The general basis of this auxiliary data set is the local hospital market or service area in which the hospital is a primary or secondary competitor.[3] Hospitals are primary competitors in market areas in which they deliver the largest portion of their output. Secondary competitors are typically larger referral centers serving a broader region comprised of several local markets that compete with institutions in each locality. Market shares, in turn, are computed for an individual hospital as the weighted average of shares over the three largest markets in which it competes, using the fractions of total output delivered to each market as weights.

The boundaries of these market areas and the share of the output of each hospital delivered to that area was delineated by analyzing patient-origin data from HCCB/ACHA discharge records. Drawing on patient-origin at level of postal zip codes from approximately 500,000

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[3] The use of geopolitical boundaries such as counties to demarcate these local areas has too many shortcomings to be a viable choice (Garnick et al., 1987; Morrisey et al., 1988; White and Chirikos, 1988). One obvious limitation is that patients cross county boundaries to obtain hospital care. A less obvious shortcoming is the implicit restriction that hospitals compete in only one "local" market.

discharge records for the last quarter of 1987, 59 market areas were demarcated.[4] Because there are more than 5,500 zip codes in the state, a simplifying algorithm was used that a) arrayed all zip codes from which at least 5 percent of a given hospital's discharges were drawn, b) arrayed all hospitals drawing at least 5 percent of their patients from each of these zip codes, and then c) repeating "a" and "b" until either there were no more hospitals to array (i.e., a self-contained market area over the geographical area encompassed by the zip codes was identified) or until it was apparent that the market included both primary and secondary competitors. In the first of these two cases, the market is comprised of only primary competitors, all service deliveries are attributed to that market, and market share is computed in any given year as the output, e.g., admissions, of the ith hospital divided by the sum of the outputs of all primary competitors, including hospital i. In the second case, the market area is comprised of both primary and secondary competitors, the output deliveries of the non-primary competitors are apportioned between and among several market areas, and the market share of the ith hospital is the weighted average of its share in its three largest markets.

Various indicators of the supply of, and demand for, health care services were then assembled for each of the local health care market areas or, in some cases, the surrounding counties. These variables are described in more detail below, and a glossary of definitions and data sources is set out in Appendix Table A.1. These measures encompass per capita physician supply as well as the availability of the types of health care providers, particularly the development of alternative delivery systems and the penetration of managed care (HMO) activities. They also include several proxy indicators for the demand for health care services, such as the proportion of the population over 65 years of age, population density (persons per square mile) and real per capita income. These measures are used below in the analysis of efficiency correlates to represent the factors in the community or external environment likely to affect efficiency-related decisions.

Analysis of Hospital Efficiency

Variable Construction

The analysis of efficiency levels of Florida hospitals requires disaggregate cost figures for constructing DEA input variables as well as the dependent and independent variables included in the cost version of the FREG model. Considerable effort went into winnowing the edited financial reports to obtain a usable set of annual expense figures.

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[4] As described above, discharge records do not go back far enough in time to define new market areas for each year of the analysis. The boundaries delineated on the basis of the 1987 data are thus assumed to be representative of all years between 1982 and 1993. However, variables based on those boundaries, e.g., market share, are constructed for each year of the 12-year period (Appendix Table A.1).

These include: 1) wage and salary payments to personnel engaged in patient care activities, subdivided by inpatient (hospital service), ambulatory and ancillary activities; 2) wage and salary payments to personnel assigned to all non-patient care centers, divided between administration (broadly defined) and a residual not-elsewhere-classified (nec) category; 3) other expenses in patient care cost centers, subdivided by inpatient, ambulatory and ancillary services; 4) other non-patient (administrative) costs attributable to capital use, i.e, depreciation charges for plant (building and land) assets, depreciation charges for fixed and movable equipment, and total interest expense on long-term and short term borrowings; 5) all other expenses in administrative cost centers; and 6) all other expenses, nec.

While most of these cost categories are straightforward, it should be noted here that the wage and salary figures do *not* include fringe benefits, which are tallied in the corresponding "other expense" categories, i.e., fringe benefits for ambulatory (patient care) personnel are included in the ambulatory, other expense grouping, etc. No feasible method was found for separating or otherwise disaggregating fringe benefits amounts from the other expense category, so this other category includes a wide range of human and capital resource expenses. It is also worth noting that excising accumulated depreciation adjustments from current year depreciation values also proved impossible (Appendix Table A.1). This problem tends generally to understate the amount of capital stock used up in the production process.

Annual cost figures for each of the above categories are scaled by a (cross-sectional) state hospital price index so as to adjust for nominal differences in input prices across hospital markets. This geographic, county-specific index relies principally on the Florida Price Level Index prepared by the State Economist's Office. It combines data on county variations in payroll costs per FTE, malpractice expenses, and various proxies for fuel, utilities etc. to produce a cross-sectional index value for the county in which the hospital is located relative to the overall State mean for any given year.

Despite some shortcomings, we pieced together a consistent set of deflators to ensure that cost figures on the *cross-section* reflect real resource values. However, this geographic index does not gauge *intertemporal* changes in factor prices. Our response to this problem is twofold: On the one hand, we use the cost data adjusted only for cross-sectional differences directly. As we shall see, the estimation of annual cross-sectional models is not necessarily influenced much by this procedure. Yet, since the pooled cross-sections or panel estimation should in principle be affected, we pieced together the PPS hospital input price index for the entire period 1982-1993 and then scaled the means of each annual cross-section by this intertemporal index. Clearly, this is not an ideal solution, but it is a feasible one. As it happens, the panel results do not differ very much, either for the DEA or FREG models, when the temporally-adjusted and unadjusted price indexes are used to deflate the cost data. Unless otherwise indicated, however, results presented below use the temporally adjusted figures.

Although only the cost figures are needed to implement the input side of the DEA model, actual rates of factor use are needed for the FREG analysis to construct factor price control variables. Figures on Full Time Equivalent (FTE) employment classified by the same patient care and administrative categories as the cost data above were divided into their counterpart cost categories to obtain three wage variables: mean wages/salaries of inpatient and ambulatory patient care personnel, mean wages/salaries of ancillary workers in patient care cost centers, and mean wages/salaries of all non-patient care (administrative) personnel. (These variables are labelled W_1, W_2, and W_3, respectively, in the analysis below). Furthermore, three capital price variables were constructed. Two of these are computed by scaling annual depreciation charges by the corresponding book value of assets at the beginning of each year, one for plant (buildings and land) and the other for fixed and movable equipment. (In the analysis below, these variables are labelled W_4 and W_5, respectively). Although a substantial effort went into the editing the book value data, some gaps doubtless remain. In preliminary work, alternative capital price variables were constructed by using available beds to scale depreciation charges in each of these subcategories. Interestingly, the analytic results do not vary significantly between estimates using the preliminary or final versions of these variables. The final factor price variable (labelled W_6 below) divided total interest payments by the value of total current, tangible and intangible assets. In effect, this yields the implicit annual interest rate on debt financing instruments of the hospital.

Finally, some effort went into constructing a meaningful set of output measures for the analyses. This was not unexpected, given the inherent problems associated with conceptualizing hospital output and finding suitable indicators of whatever is conceptualized (Ehreth, 1994). What may be important to reiterate here, however, is that the output measures also had to meet the demands of the estimating models, particularly the DEA model, for continuously measured, appropriately scaled, and positive levels of output. After some preliminary experimentation, six measures were ultimately selected, four relating to the production of inpatient services and two others gauging the production of outpatient services. See Appendix Table A.1.

The inpatient measures attempt directly to index activity levels in the facility and indirectly to account for two dimensions of hospital case mix: severity of medical conditions and distribution of patients by payor group. One of the inpatient variables scales total admissions in a given year by mean DRG-weights for the same year (Appendix Table A.1). It reflects the interaction between the number *and* severity of cases admitted to each facility. The other three (inpatient) variables measure the number of post-admission patient days (i.e., inpatient days net of the day of admission) by payor category. One gauges the days for which Medicare was the primary payor, another the days for which Medicaid was the primary payor, and the third measures the residual number of patient days attributable, in effect, to Blue Cross, other private payor groups, and self-pay patients. We believe these four variables adequately gauge the level and structure of hospital inpatient

activity as well as the impact over the study period of cost containment efforts on the average case mix associated wi' that activity. (In the analysis below, the Medicare, Medicaid and Other Payor measures are labelled Q_1, Q_2, and Q_3, respectively, and the case mix-weighted admissions variable is labelled Q_4).

The two outpatient measures are slightly more complicated. Each is predicated on the common practice of constructing a composite measure of hospital output by weighting some indicator of outpatient activity by the ratio of mean prices of that outpatient service to an inpatient output measure (e.g., admissions) and then adding this inpatient-equivalent outpatient output to admissions to obtain a measure of "adjusted admissions." (Simple arithmetic shows that this method is equivalent to multiplying admissions by $\{1 + rr\}$, where rr = the ratio of revenue generated in outpatient and inpatient centers). One outpatient measure (labelled Q_{5t} below) is thus calculated as follows:

$$Q_{5t} = (A_t (1 + rr_{5t})) - A_t \qquad (1)$$

where A_t represents admissions to the hospital in year t and rr_{5t} represents the ratio of outpatient revenue generated in ancillary or inpatient cost centers to total inpatient revenue in year t. This variable gauges primarily the level of outpatient activity attributable to special tests and procedures (e.g., MRI, C-T scan, cardiac catheterization, physical therapy, etc.), much of which is doubtless provided either pre- or post-inpatient episode to hospital inpatients in a given year. The level of such activity, consequently, is cast in case-equivalent terms.

In contrast, the second outpatient variable (labelled below Q_{6t}) measures the level of activity in ambulatory centers generating outpatient revenue in emergency room-equivalent terms. Preliminary work attempted to use several physical measures of ambulatory services directly, e.g., the number of ambulatory surgery services, ambulance services, etc., but estimation problems were encountered because of the large number of zero values. Accordingly, a measure of the revenue ratio between all ambulatory activity other than emergency services (including both inpatient and outpatient renal dialysis services) and emergency services was constructed, and an "adjusted" emergency visit variable was created to represent the level of ambulatory outpatient activity. Letting (rr_{6t}) represent this more disaggregate revenue ratio and ER_t the number of emergency service visits in year t, the second outpatient indicator in ER visit equivalents is constructed as follows:

$$Q_{6t} = ER_t (1 + rr_{6t}) \qquad (2)$$

Model Specification

Data Envelopment Analysis

The final DEA model was specified as follows:

$$DEA = \frac{Q_1Y_1 + Q_2Y_2 + Q_3Y_3 + Q_4Y_4 + Q_5Y_5 + Q_6Y_6}{C_1X_1 + C_2X_2 + C_3X_3 + C_4X_4 + C_5X_5 + C_6X_6} \qquad (3)$$

The six output weights are represented by Y_1-Y_6 and the six input weights are depicted by X_1-X_6. The variables Q_1-Q_6 represent the output variables and C_1-C_6 represent the input variables.

The input variables used here are as follows:

- C_1 = the sum of the inpatient, ambulatory and ancillary wage bills for patient care. This variable represents direct patient care expenses.
- C_2 = the sum of the administrative portion of the wage bill plus the residual amount not already accounted for in C_1. This variable captures the administrative and general expenses of patient care.
- C_3 = the sum of inpatient, ambulatory and ancillary <u>other costs</u> of patient care.
- C_4 = depreciation expenses for plant (facilities and land) as defined in the previous section.
- C_5 = the equipment expense for a year calculated in the same manner as C_4, except using fixed and movable <u>equipment</u> depreciation charges.
- C_6 = all other costs of a hospital in one year. This is the sum of total interest expense and miscellaneous other costs.

Thus, the input variables used here provide a relatively inclusive set of input costs for the panel hospitals. Both inpatient and outpatient patient-care expenses were included, as well as the costs of facilities, equipment, supplies, capital, etc.

The output variables used in the final DEA model are those defined in the preceding section on variable construction, viz.,

- Q_1 = the sum of post-admission Medicare inpatient days.
- Q_2 = the sum of post-admission Medicaid inpatient days.
- Q_3 = the total number of post-admission inpatient days in all other payor categories.
- Q_4 = the case mix-weighted admissions index.
- Q_5 = the case-equivalent outpatient index defined above.
- Q_6 = the emergency service-equivalent index defined above.

As discussed above, these output variables provide a reasonably comprehensive measure of the medical production activities of the hospitals including emergency, outpatient and inpatient services.

The general DEA model for measuring the overall performance of the panel hospitals was of the following form:

$$\text{Max } h_0 = \frac{\Sigma_r u_r y_{r0}}{\Sigma_i v_i x_{i0}} \tag{4a}$$

Subject to:

$$\frac{\Sigma_r u_r y_{rj}}{\Sigma_i v_i x_{ij}} <= 1;$$

$(j = 1, \ldots, n;\ u_r,\ v_i >= 0;\ r = 1, \ldots, 6;\ \ i = 1, \ldots, 6).$

Here y_{rj}, x_{ij} (all positive) are the outputs and inputs of the jth DMU, n is the number of hospitals studied, and u_r, $v_i >= 0$ are the variable weights which were determined by the linear programming algorithm in solving the problem. This model follows previous work by Charnes, et al.(1978, 1981, 1984) and the somewhat more recent application by Boussofiane, et al. (1991).

The above model was transformed into a linear programming problem as follows:

$$\text{Max } \ h_0 = \Sigma_r u_r y_{r0} \tag{4b}$$

Subject to:

$$\Sigma_r u_r y_{rj} - \Sigma_i v_i x_{ij} <= 0$$

$$\Sigma_i v_i x_{i0} = 1$$

$(j = 1, \ldots, n;\ u_r,\ v_i >= 0;\ \ r = 1, \ldots, 6;\ \ i = 1, \ldots, 6).$

The model was used to solve for the weights u_r and v_i so as to maximize the efficiency of each unit. Then, the DEA efficiency rating h_0 was calculated associated with the weights. Units with an efficiency rating less than 1.0 were considered as inefficient compared to those units with efficiency ratings equal to 1.0. The above model was used to measure the overall performance of various subgroups of the panel hospitals, as described more fully below in the section on sample partitions.

Frontier Regression

As described previously, we use frontier regression methods to estimate hospital inefficiencies as stochastic deviations from *best-practice* technique. Inefficiency is modeled as a composable error term

in two parts: one attributable to chance factors or "noise" and the other attributable to systematic variations that are assumed to be distributed in a particular way--in what follows as the half-normal distribution.[5] Notwithstanding its stochastic element, the FREG model is specified in a manner generally consistent with the DEA model so as to facilitate comparisons in the results of the two methods. The frontier model directly uses the same vector of **Q** output variables (Q_1 - Q_6 defined above), but it rearranges the vector of input variables and aggregates all cost elements to obtain the conventional econometric cost function as represented in equation (5a):

$$TC = f\{\mathbf{Q}, \mathbf{W}; \mathbf{B}, \exp(v + u)\} \qquad (5a)$$

Here TC represents total costs, which is now the dependent variable, and **W** represents a vector of factor prices (W_1 - W_6 defined above), which along with **Q** are now independent variables. The **W** vector is obtained by dividing the specific cost categories described above by the factor inputs corresponding to those categories, e.g., the patient care wage bill by the number of FTE personnel in patient care cost centers. The **B** in (5a) is the parameter vector, the v is a random disturbance term representing statistical noise, and the u is the half-normal error term from which the inefficiency residual or score is derived, each to be estimated by maximum likelihood methods.

The actual estimation of econometric cost functions, however, is substantially more complicated than equation (5a) suggests. The primary reason is that modeling only the main effects of the output and factor price variables in a regression framework implies unacceptable restrictions on important parameters of the underlying cost function, e.g., the substitution and scale characteristics of the function. Since it is never entirely clear how best to model the structural characteristics of these functions, flexible forms have become quite popular in the econometric literature. The translog function (a second order Taylor Series expansion approximating some true but unknown generalized log cost function) is the best known and increasingly most commonly used form (cf., Chambers, 1988; Berndt and Christensen, 1978). It may be represented generally as follows:

$$tc = f'\{\mathbf{q}, \mathbf{w}, \tfrac{1}{2}(\mathbf{q}^2, \mathbf{w}^2, \mathbf{q}_i\mathbf{q}_k, \mathbf{w}_j\mathbf{w}_l, \mathbf{q}_j\mathbf{w}_l); \mathbf{B}, v+u\} \qquad (5b)$$

where the lower case letters are the natural logarithms of the upper case variables in equation (5a), i and k index the output variables (i ne k), j and l index the factor price variables (j ne l) and, as before, **B** is the parameter vector, and ($v + u$) the composable error term to be estimated.

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[5] See, especially, Aigner et al. (1977) who developed the methodology. Also see Bauer (1990) and Cornwell et al. (1990). From an operational point of view, a major breakthrough was the development of computer software by William Greene (1992) capable of estimating frontier functions and their associated inefficiency residuals.

As can be seen, flexible translog functional forms encompass a large number of squared and cross-product terms--as a rule of thumb, about {(q + w)(q + w +1)/2} number of such terms in an estimating equation with *q* number of output and *w* number of input (factor price) variables. Although econometricians frequently finesse the problems associated with the resulting large number of regressors by invoking Shephard's Lemma to estimate just factor share equations, we concluded that such indirect estimation in the present study would make the already vexing problems of interpretation and comparison even more difficult (cf., Cowing and Holtman, 1983). We also learned in preliminary work that estimating a frontier regression comprised of six outputs and six factor price variables with a *complete* set of interaction and cross-product terms for annual cross-sections of the Florida panel data (N=186) produced either questionable results or, sometimes, no results at all.[6] We were thus forced to impose some structure on the cost model. Our general strategy in doing so may be briefly described as follows.

To begin with, we made every effort to estimate the most general model possible, keeping as many higher-order terms as possible in order to portray realistic non-linearities in the cost consequences of changing output/input relationships. We then experimented with several model specifications that excluded some, but not all, of the higher-order terms. One version included all squared terms, but limited cross-products only to output variables. That is, we estimated the following partial version of the translog model:

$$tc = \alpha_0 + \Sigma_i \beta_i q_i + \Sigma_j \gamma_j w_j + \tfrac{1}{2}(\Sigma_i \beta_{ii} q_i q_i + \Sigma_j \gamma_{jj} w_j w_j + \Sigma_i \Sigma_k \beta_{ik} q_i q_k) + v + u \qquad (6a)$$

(i,k = 1, 2, , 6; j = 1, 2, , 6; i ne j,k) ;

where the lower case **q** and **w** notation for the logarithms of the output and factor price variables is defined above, the α, β, and γ are parameters to be estimated by maximum likelihood, the $(v + u)$ is the composable error. We refer below to this formulation as FREG model "**A**." Since it yielded reasonable results (especially better results than those yielded by the alternative in which the complete set of (ln Q * ln W) cross-product terms are included), it is one of the models that we draw on to calculate inefficiency residuals.

Given the large number of parameters that remain in equation (6a), and the fact that some standard economic properties are missing in partial models of this sort, we also experimented with simpler, but more structured, cost functions. One that yielded reasonable results is a

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[6] The computer program simply falls back to OLS estimation if the residuals have the "wrong" skew. Even when the residuals are retrieved from the estimation, the skewness of the error term may impart bias to the results. See, for example, Skinner (1994).

Cobb-Douglas hybrid that imposes the restriction that the cost function is homogeneous of the first degree in factor prices and reduces the number of parameters to be estimated by creating a "common" set of higher order terms for a select subgroup of outputs. More specifically, we estimated the following model:

$$tc = \alpha_0 + \Sigma_i \beta_i q_i + \Sigma_{j*} \gamma_{j*} w_{j*} + \tfrac{1}{2}(\Sigma_i \beta_{ii} q_i q_i + \beta z^2 +$$

$$\Sigma_k \beta_{kz} q_k z) + (v + u) \qquad (6b)$$

(i, = 1, 2, , 6; j^* = 1, 2, , 6; $k=i|i$ = 1,2,3; k ne $i|i$ = 4,5,6; (i ne j); $\Sigma_j \gamma_j = 1$); $Z = \Sigma_k Q_k$, and $z = \ln Z$ as defined above.[7] We refer to this version as FREG cost model "B" and we also use it to compute inefficiency residuals.

As will be seen, estimated FREG inefficiency residuals are highly correlated. The results, in fact, tend generally to be bracketed by Models "A" and "B," so we rely primarily on those models in the rest of the study. However, we also tested the sensitivity of the FREG model to somewhat different specifications and measures of outputs and inputs.[8] Because it plays a role in the subsequent analysis of efficiency correlates, one version worth noting here is an estimate of Equation (6a) wherein hospital-specific wage rates are replaced by the means of these factor prices in each hospital's primary market. This model, labelled model "AW" below, tests the impact of allocative inefficiencies on costs. As anticipated, models such as "AW" yield different results, though they are not as different as might otherwise be supposed.

Estimating the parameters of the FREG translog cost function is simply the first of two steps required to obtain the inefficiency residual. The second step uses the estimated parameters to compute mean inefficiency. Since the mean of v is by assumption zero, the mean of u is readily obtained. It is added to the predicted costs of each hospital observation, and these predicted costs are then summed over all observations. The composable error ($v + u$) is subsequently computed by subtracting observed costs from predicted costs. Now Jondrow et al. (1982) developed a method for computing the expected value of u for each observation, conditional on the composable error and an assumption about the underlying distribution governing the behavior of u. Assuming that

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[7] The common Z vector refers to the three payor-related patient day variables Q_1 -Q_3 defined above. The other output measures Q_4 -Q_6 are unchanged in this specification.

[8] It should be noted here that we also estimated a model that included a trend variable as a regressor. Interestingly, the results from this model do not vary much at all with the other models, though the time variable is significantly positive as expected. The inefficiency residuals from that model are highly correlated with those derived from other versions of the FREG specification, e.g., the Pearson coefficient between this specification and FREG model "B" is 0.96.

this latter distribution is the half-normal (and of course that the distribution of *v* is normal) Jondrow et al. compute an observation-specific inefficiency residual as:

$$E[u|\epsilon] = \sigma\lambda/(1 + \lambda^2)\ [\phi(\epsilon\lambda/\sigma)/\Phi(\epsilon\lambda/\sigma)\ -(\epsilon\lambda/\sigma)] \qquad (7)$$

where $\lambda = \sigma_u/\sigma_v$ and $\sigma = \{(\sigma_v)^2 + (\sigma_u)^2)\}^{½}$ and ϕ and Φ are, respectively the probability density and the cumulative density functions of the standard normal distribution.[9] The method worked out by Jondrow and his colleagues is quite significant, for it paved the way for making the frontier regression approach useful in a wide range of applications other than simply aggregate analyses of industry-wide efficiency.

Finally, given the translog specification, note that residual inefficiency is computed as the proportional difference between the costs of a given hospital and the frontier or *best-practice* cost level, and corresponding that *u* is scaled from zero upwards. For example, a residual of 0.05 is interpreted as a 5 percent differential between the observation and the frontier level, i.e., the expected value of *u* for that observation, conditional on the estimated composed error and the normal/half-normal distribution of *v* and *u*. DEA efficiency is computed in mirror image terms, i.e., most efficient hospitals take the value of one and the correspondingly lower efficiency is interpreted proportionally, e.g., 80 percent or four-fifths as efficient as the estimated DEA frontier. In order to simplify the narrative from this point on, we invert the frontier residual so that it is nominally scaled in the same direction as the computed DEA value. We refer to the inverted residual as the frontier *score* and, when comparing it to the DEA value, refer to both as efficiency *scoring*. We reserve the use of the term inefficiency *residual* for the computed (i.e., non-inverted) frontier value.

Sample Partitions

The panel data set on 186 Florida hospitals for the period 1982-1993 described earlier can be exploited in different ways for purposes of estimating the DEA and FREG models. Since the analysis is ultimately interested in understanding trends in hospital efficiency levels, a particularly important question is whether the "frontiers" should be estimated separately for, say, each year over the 12-year period or for fewer periods using pooled data--say, twice for the first and second halves of the period or once for the 2232 observations comprising the entire longitudinal data set. This is crucial substantively in terms of identifying the underlying technological regime that is being tapped in the estimation. It is also crucial logistically, because the estimation

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[9] It is possible to compute the inefficiency residual conditional on several different underlying distributions. We experimented with the exponential distribution that is also part of the frontier routine included in Greene (1992), but found that the results were quite similar to those yielded by the half-normal. As a result, we restrict our attention in the following to just the half-normal.

of DEA scores on pooled data turns out to be extremely tedious and time-consuming.

Nonetheless, we decided to estimate models for both the 12 annual cross-sections of the 186 hospitals in continuous operation over the period 1982-1993 and for the pooled cross-sections of 2,232 hospital-year observations corresponding to the same period. (Recall that we refer to the latter group of hospitals as the panel sample). As will be seen, some difficulties arose in the estimation of some cross-sectional models, in part because of the limited number of observations on any given annual cross-section. While the cross-sectional results are of course reported, we rely more heavily on the full panel estimates in drawing inferences from the analysis. Among other things, this assumes that all Florida hospitals over this period faced identical technological constraints or choices. This does not appear to us to be an unreasonable assumption. We test this assumption below by comparing annual cross-sectional results to panel estimates referring to (conditioned on) individual years.

As will also be seen, we estimated several "stratified" versions of the DEA and FREG models, i.e., separate models for partitions of the panel sample defined in terms of hospital control categories and bed size distribution. Although important in their own right, there was insufficient time available to estimate a more complete set of models corresponding to various policy-relevant strata. The results of the more limited attempt to estimate stratified models are presented here only for purposes of interpreting some of the main findings. More detailed analysis of stratified models is left for future work.

Empirical Findings

Some Descriptive Data

This subsection provides a brief descriptive account of the variables used in estimating the DEA and FREG models as a backdrop against which to judge the analytic results set out later on. Tables 2, 3 and 4 present, in turn, descriptive information on output indicators, hospital inputs, and nominal hospital costs for panel hospitals for the entire period 1982-1993 as well as for selected annual cross-sections over that period. These summary data are noteworthy in at least three different ways:

To begin with, there is mixed evidence about the extent to which the panel hospitals actually grew between 1982 and 1993. On the one hand, inpatient cases on average fell over most of the period, showing only a slight upturn after 1990, while inpatient days fell steadily, from about 66,000 in 1982 to 53,000 in 1993 for the average panel hospital. Note also that the number of available beds changed very little, though there do appear to be some reallocations in product lines outside of the traditional medical/surgical activities. On the other hand, health conditions of admitted patients grew more severe so that the case mix-weighted admissions index rose steadily over the period. There were

Table 2
Selected Output Indicators By Type, All Panel Hospitals, Selected Years, 1982-1993

Indicator[a]	Mean Number or Percent By Year							
	1982-1993	1982	1984	1986	1988	1990	1992	1993
Inpatient: Admissions								
Number	8287	8793	8761	8256	8032	7981	8138	8304
Percent	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Medicare	46.0	43.9	45.4	44.3	43.9	46.4	49.8	50.4
Medicaid	7.6	5.1	5.2	5.1	7.1	9.6	11.4	12.7
Charge-Based	39.5	49.9	48.3	48.6	46.9	29.1	23.0	19.9
Other Payors	6.9	1.0	1.1	2.0	2.2	14.9	15.8	17.0
Inpatient: Patient Days								
Number (000)	57.8	66.1	61.4	57.1	56.5	55.5	54.5	52.9
Percent	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Med/Surg Acute	74.6	82.8	80.2	75.6	72.5	70.7	69.4	69.6
Other Patient Days	25.4	17.2	19.8	24.4	27.5	29.3	30.5	30.4
Outpatient								
Emergency Services (000)	19.8	16.6	17.0	18.5	20.3	21.5	22.7	23.8
Ambulance Services	521	338	358	402	524	729	622	667
Ambulatory Surgeries (000)	120.7	22.2	49.0	85.0	142.7	173.7	203.4	207.7
Dialysis Treatments	985	748	726	902	1026	986	1141	1254
Composite Output Indexes								
Case Mix-Weighted Admissions	9400	8735	9050	8816	9221	9743	10471	10842
Outpatient (Case Equivalents)	1366	617	778	1080	1440	1705	2122	2347
Outpatient (ER Equivalents/1000)	42.2	24.9	27.8	33.2	44.0	49.1	63.6	69.0
N	2,232	186	186	186	186	186	186	186

a. See Appendix Table A.1 for variable definitions.

Table 3
Selected Hospital Inputs By Type, All Panel Hospitals, Selected Years, 1982-1993

Inputs[a]	Mean Number/Value or Percent By Year							
	1982-1993	1982	1984	1986	1988	1990	1992	1993
FTE Personnel								
Number	784.7	704.9	716.1	718.6	760.0	845.0	905.3	921.0
Percent	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Patient Care	60.6	60.7	59.8	59.0	60.0	60.9	62.5	63.2
Hospital Services	32.5	37.1	35.0	32.3	31.6	30.8	30.1	29.9
Med/Surg	21.5	28.1	24.7	21.1	19.6	18.7	17.9	17.6
Other	11.3	9.0	10.3	11.2	12.0	12.1	12.2	12.4
Ambulatory Services	5.2	3.5	3.7	4.4	5.4	5.9	7.0	7.7
Ancillary Services	22.9	20.1	21.1	22.3	23.1	24.2	25.4	25.6
Administration	39.4	39.3	40.2	41.0	40.0	39.1	37.5	36.8
Beds								
Number (Available Beds)	250	239	246	247	249	253	258	256
Percent	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Acute/Intensive	99.1	99.8	99.9	99.6	98.8	98.7	98.2	98.0
Med/Surg	77.2	81.7	80.7	78.7	76.1	74.8	73.0	72.6
Other	21.9	18.1	19.2	20.8	22.7	23.9	25.2	25.4
Subacute	0.9	0.2	0.1	0.4	1.2	1.3	1.8	2.0
Capital Assets ($ Millions)								
Plant and Related	22.0	11.9	14.7	19.2	22.6	26.9	31.3	33.3
Equipment	16.6	8.9	9.9	13.5	17.4	20.2	24.5	27.2
N	2,232	186	186	186	186	186	186	186

a. See Appendix Table A.1 for variable definitions.

Note: Percentages may not add up due to rounding.

Table 4
Nominal Hospital Expenses By Category, All Panel Hospitals, Selected Years, 1982-1993

Category[a]	Mean Expense or Percent By Year							
	1982-1993	1982	1984	1986	1988	1990	1992	1993
Total Expenses ($ Millions)	44.2	24.9	30.6	35.7	43.2	54.4	64.5	68.3
Percent	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Wages and Salaries	39.9	43.8	41.8	38.8	38.3	39.0	39.4	39.2
All Other	60.1	56.2	58.2	61.2	61.7	61.0	60.6	60.8
Wages and Salaries ($ Millions)	18.2	11.4	13.3	14.5	17.3	22.1	26.1	27.5
Percent	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Patient Care	65.8	64.6	64.1	63.7	65.4	67.5	68.7	69.0
Hospital Services	34.9	38.4	36.9	34.3	34.3	34.4	32.9	32.3
Ambulatory Services	5.8	3.9	4.2	4.8	5.9	6.6	8.0	8.9
Ancillary Services	25.1	22.3	23.1	24.5	25.2	26.5	27.8	27.8
Administration	34.2	35.4	35.8	36.3	34.6	32.5	31.3	31.0
All Other Expenses ($ Millions)	26.0	13.5	17.3	21.2	25.9	32.4	38.3	40.8
Percent	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Patient Care	41.0	41.4	40.1	37.9	40.0	42.5	44.1	44.0
Hospital Services	6.7	7.2	6.3	6.2	6.9	7.3	6.6	6.5
Ambulatory Services	2.3	1.6	1.6	1.8	2.3	2.9	3.3	3.5
Ancillary Services	31.0	32.7	32.1	29.8	30.8	32.2	34.2	34.0
Administration	59.0	58.6	59.9	62.1	60.0	57.5	55.9	56.0
Capital	15.9	14.9	15.2	16.4	16.7	17.0	15.0	14.8
Other	43.1	43.6	44.7	45.8	43.3	40.5	40.9	41.2
N	2,232	186	186	186	186	186	186	186

a. See Appendix Table A.1 for variable definitions.

Note: Percentages may not add up due to rounding.

also significant increases in outpatient service deliveries, at least those selected items included in the third panel of Table 2. More important, there was a steady rise in the average number of Full Time Equivalent personnel in these hospitals, as the top-most panel in Table 3 shows. The increases here, not surprisingly, were in areas outside of traditional, patient care centers, especially ambulatory and ancillary services. Although the data are subject to substantial measurement error, the bottom panel shows a steady rise in the (nominal) book values of plant assets and equipment. When coupled to the growing FTE work force, the clear implication is input utilization rates increased over time.

Second, in addition to the changing levels of outputs, inputs, and costs, there is considerable evidence that structural changes occurred in output and input categories. Consider, for instance, the distribution of admissions by payor category in Table 2. Whereas the odds were just about even that a case (admission) would have a charge-based payor in 1982, those odds increased substantially by 1993, in part because of dramatic changes in the proportions of cases reimbursed by either the Medicare or Medicaid programs, and in part because of the increasing likelihood of payor discounting--a practice categorized in the "Other Payor" grouping in Table 2. Payor distribution changed equivalently for patient days, which explains its use in constructing payor-specific output indicators for the statistical analysis. Other structural charges are also apparent. Note the sizable reduction in the proportion of patient days accounted for by acute medical-surgery (med/surg) patients as well as the significant increase in ambulatory surgeries in the mix of selected outpatient activities presented in Table 2. Indeed, the rapid increases in the composite outpatient indexes relative to the composite admissions index in the bottom-most panel of Table 2 illustrate most dramatically the structural changes in hospital output, accounting as well for their inclusion as output indicators in the statistical work.

Finally, whether attributable to more intensive utilization of inputs or structural changes in outputs, hospital expenses have clearly risen for the period under study, as Table 4 shows. In examining the distribution of total expenses between wages and salaries, on the one hand, and all other items on the other, recall that fringe benefits are included in the all other category. Also bear in mind that we include "capital" expenses (i.e., depreciation charges against plant and equipment as well as long and short-term interest payments) in the administrative expenses category. These matters aside, what is perhaps most interesting here is that the cost structure of hospitals does not appear to have changed much over the period in question. To be sure, the average fraction of wage and salary expense accounted for by traditional inpatient (hospital) services fell between 1982 and 1993, and correspondingly ambulatory and ancillary services rose. Yet, the distribution between wages and the other category as well as the distribution of the "all other" category itself is not altogether different in 1993 then it was a decade earlier--at least in this panel sample of hospitals. For this reason, it is unclear whether efficiency relationships in this

set of institutions has actually changed very much over the period in question. Clearly, that is for the DEA and FREG analyses to explain, topics to which we now turn.

DEA Results

Results from the Data Envelopment Analysis show a reasonable level of consistency over time for both cross-sectional and pooled estimates. In general, the results also appear to have reasonable face validity. Figure 7 indicates that the pooled estimates relative to the cross-sectional ones produced consistently lower levels of observed efficiency over the entire period of study, though this is likely to be an artifact of the pooled run in which each DMU was competing with 2231 other DMU's simultaneously, as opposed to the cross-sectional runs in which each DMU was competing with only 185 others at one time. There was both a divergence in direction and magnitude between the sample partitions over most of the time period, with the pooled estimates showing both decreasing and lower levels of efficiency. The greatest divergence in mean scores produced by the alternative runs occurred in 1990, when the absolute difference was .23.

Table 5 shows the mean scores and standard deviations for each year. It should be noted that a theta value of 1 is given to the subset of hospitals found to be technically efficient, and all the others have scores with values between 0.0 and 1.0. As Figure 7 also showed, the cross-sectional results produced virtually no trend in efficiency change over the 12-year period, while the pooled runs produced a definite declining trend in efficiency over this period of time. The Pearson correlation coefficient between the estimates portrayed in Figure 7 (DEA Cross-Section:DEA Pooled, N=12) is -.7568 ($p < .004$), indicating the divergence between the efficiency results produced by the two DEA methods. It should be noted that this correlation is based on only 12 data points. When the full data set is used (N= 2232) the Pearson coefficient is .3596 ($p < .0001$), which gives the opposite view of the relationship between the cross-sectional and pooled results. Whether efficiency was actually declining from 1982-1993 as the pooled results showed, or whether efficiency was virtually unchanged over this period of time as the cross-section results showed, is unclear. Given that the cross-sectional results were obtained by running the DEA model 12 times, with identical variables and year-specific data, i.e., each run was independent, it is likely that the decline in DEA scores over time shown by the pooled approach is a methodological artifact. Another fact lending credence to this interpretation is that there is an obvious temporal trend in the standard deviations for the pooled method, with a clear increase from .1139 in 1982 to .1694 in 1993. There is no such trend for the standard deviations in the cross-sectional data, though there is a slight decrease over this time period. Because the upper bound for the DEA scores is fixed at 1.0, the changes in means and standard deviations are due to the magnitudes and number of low scores. Table 5 also shows that minimum scores in the pooled data decreased on a regular basis from 1982 through 1993, while minimum scores in the cross-sectional data showed no such pattern. Also, the two low scores

Figure 7

Cross-Section and Pooled Mean DEA Scores

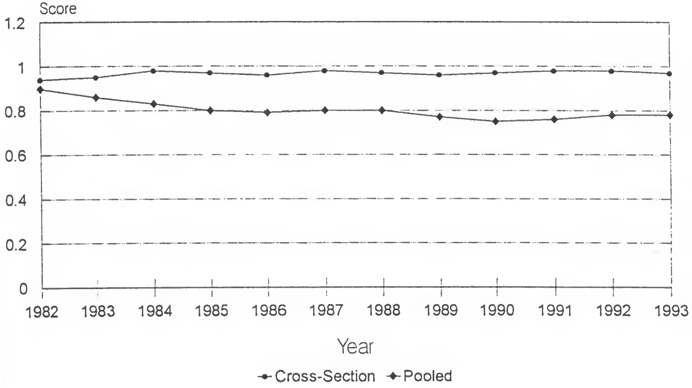


Table 5
Summary Statistics, DEA Efficiency Scores,
All Panel Hospitals, 1982-1993

Year/Sample Partition		N	Mean Score	Standard Deviation	Minimum	Maximum
1982	Cross-section	186	.9394	.0947	.6157	1.0000
	Pooled	186	.9033	.1139	.5823	1.0000
1983	Cross-section	186	.9523	.0766	.6671	1.0000
	Pooled	186	.8568	.1195	.5925	1.0000
1984	Cross-section	186	.9750	.0596	.7110	1.0000
	Pooled	186	.8272	.1223	.5835	1.0000
1985	Cross-section	186	.9677	.0710	.7003	1.0000
	Pooled	186	.7997	.1304	.5197	1.0000
1986	Cross-section	186	.9604	.0919	.3845	1.0000
	Pooled	186	.7913	.1324	.5612	1.0000
1987	Cross-section	186	.9782	.0605	.6419	1.0000
	Pooled	186	.8031	.1383	.5338	1.0000
1988	Cross-section	186	.9718	.0567	.7508	1.0000
	Pooled	186	.7990	.1397	.5087	1.0000
1989	Cross-section	186	.9641	.0907	.3947	1.0000
	Pooled	186	.7696	.1511	.4845	1.0000
1990	Cross-section	186	.9702	.0683	.6509	1.0000
	Pooled	186	.7491	.1545	.2743	1.0000
1991	Cross-section	186	.9801	.0528	.7218	1.0000
	Pooled	186	.7550	.1597	.4339	1.0000
1992	Cross-section	186	.9829	.0538	.6713	1.0000
	Pooled	186	.7777	.1600	.4708	1.0000
1993	Cross-section	186	.9740	.0667	.5521	1.0000
	Pooled	186	.7815	.1694	.4189	1.0000
Pooled All Years		2232	.8011	.1477	.2743	1.0000

in the cross-sectional analysis (1986 and 1989) were obviously aberrations, because the means in those years were virtually unaffected. Thus, the pooled estimates result in a higher proportion of low DEA scores over time than do the cross-sectional estimates.

Frontier Regression Results

Tables 6, 7 and 8 present distillations of the extensive set of results from the estimation of the frontier regression models. Table 6, for instance, presents a selected subset of cost elasticities calculated from estimated regression coefficients of translog specifications A and B, i.e., equations (6a) and (6b) above, for various sample groupings. The complete estimating equation and test statistics for the entire period 1982-1993 as well as for selected annual cross-sections are presented in Appendix Tables A.2 and A.3. In order to simplify matters, these Appendix Tables list coefficients by the notation and index values given in equations (6a) and (6b). Thus, in Appendix Table A.2, β_4 is the estimated coefficient on the natural logarithm of the case mix-weighted admissions (Q_4) variable, γ_{33} is the estimated coefficient on the squared log W_3 administrative wage variable (i.e., $w_3 * w_3$), and β_{56} is the coefficient on the cross-product effect of the two composite outpatient indexes, Q_5 and Q_6 (i.e., $q_5 * q_6$), etc.

Perhaps the most noteworthy aspects of the elasticities in Table 6 are that a) they have the right signs, b) they appear in most cases to have reasonable magnitudes, and c) they do not differ dramatically between the two versions of the FREG estimating model. Although several of the first-order output and factor price terms have negative signs, the elasticities are as expected positive, at least when evaluated at the sample means. For example, the elasticity of total costs with respect to the case mix-weighted admission variable (i.e., $\partial \ln TC/\partial \ln Q_4$) is 0.374 in the panel estimate of Model B, despite the negative sign on the first-order Q_4 term in Appendix Table A.3. The magnitudes of these elasticities also seem to be reasonable, as evidenced, say, by the differences between the cost consequences of changes in inpatient and outpatient output as well as by differentials in the structure of these outputs over time. Although the elasticities for each of these variables do differ between the two models, the differences are not as great as might have been expected, given the larger number of higher-order terms included in the specification of Model A than in Model B. Indeed, despite the large number of parameters and attending multicollinearity, the estimated parameters of the more complete translog cost model appear to be quite reasonable. While there are surely differences in the predicted costs (used in computing the inefficiency residual) yielded by the two specifications, the results tend to be more consistent than not. Variations in results discussed below are thus unlikely to be attributable to the particular specification chosen for the FREG model.

Table 7 provides further evidence of the close similarity in the results of various specifications of the FREG translog model, showing summary statistics for the computed inefficiency residuals of different model specifications and time points. The means for the entire panel of 2,232 observations are close to each other, though the standard deviations vary somewhat. The differences appear to be related to the

Table 6
Selected Cost Elasticities, By FREG Model and Selected Time Periods[a]

Determinant/Model[b]	Estimated Elasticities at the Means			
	Panel	Annual Cross-Section		
	1982-1993	1993	1987	1982/83
Admissions (Case Mix-Weighted Index)				
Model A	0.498	0.502	0.224	0.550
Model B	0.374	0.494	0.358	0.529
Outpatient Index (Case Equivalents)				
Model A	0.196	0.129	0.063	0.654
Model B	0.168	0.140	0.068	0.039
Administrative Wages and Salaries				
Model A	0.252	0.337	0.491	0.457
Model B	0.479	0.548	0.542	0.602

a. See Appendix Tables A.2 and A.3 for the complete estimating equations and test statistics for these translog cost regression results.

b. See text equations (6a) and (6b) for the model specifications and Appendix Table A.1 for variable definitions.

Table 7
Estimated Inefficiency Residuals, By FREG Model and Selected Time Periods[a]

Model Specification[b]	Mean Inefficiency Residual (Standard Deviation)			
	Panel	Annual Cross-Section		
	1982-1993	1993	1987	1982/83
Model A	0.143 (0.077)	0.148 (0.126)	0.170 (0.120)	0.064 (0.019)
Model B	0.161 (0.094)	0.161 (0.113)	0.170 (0.113)	0.104 (0.044)
Model AW	0.137 (0.073)	0.157 (0.073)	0.097 (0.047)	0.0511 (0.012)

a. For Models A and B, see Appendix Tables A.2 and A.3 for the complete estimating equations and test statistics for the translog cost regressions used to obtain these inefficiency residuals.

b. See text equations (6a) and (6b) for the model specifications, the text for a description of Model "AW, and Appendix Table A.1 for variable definitions.

Table 8
Correlation Coefficients for Inefficiency Residuals, By FREG Model, Panel Specification, 1982-1993[a]

Model Specification	Coefficient (Prob.) Model A	Model B	Model AW
Pearson Coefficient			
Model A	1.00 (0.0)	-	-
Model B	0.892 (0.0001)	1.00 (0.0)	-
Model AW	0.876 (0.0001)	0.766 (0.0001)	1.00 (0.0)
Spearman Coefficient			
Model A	1.00 (0.0)	-	-
Model B	0.903 (0.0001)	1.00 (0.0)	-
Model AW	0.842 (0.0001)	0.758 (0.0001)	1.00 (0.0)
N	2,232	2,232	2,232

a. See notes to Table 7 above.

variations in the models used to derive them. Model "A" yields a mean inefficiency level about 0.2 percentage points lower than Model "B," most likely because it imposes fewer restrictions on the parameters of the cost function. The "AW" model, which replaces hospital-specific factor prices with local market means, suggests that variations in hospital wage policies appear to raise mean inefficiency by about 0.05 percentage points. In all cases, however, these estimates imply that hospital costs are on average about 15 percent higher than the frontier level.

It should be noted in this regard that the efficiency residuals are in most cases statistically significant, as evidenced by the test statistics on the parameters on the distributions of the disturbances ($\sigma_u/\sigma_v = \lambda$ and $\{(\sigma_v)^2 + (\sigma_u)^2)\}^{½} = \sigma$) in Appendix Tables A.2 and A.3, and they are generally larger in magnitude than the error component attributable to statistical noise. Computed variance components for the panel estimates of Models A and B, for instance, show that inefficiency accounts for 57.1 and 62.5 percent, respectively, whereas statistical noise accounts for just 42.9 and 37.5 percent, respectively, of the residuals. The variations in the cross-sectional means, and the absence in several cases of statistically significant distribution parameters, are less easy to understand. Higher efficiency levels in the early 1980s relative to the early 1990s may reflect growing inefficiencies associated with more complex service delivery. We return to this question below.

Despite the cross-sectional variations, Table 8 shows that the panel estimates are nonetheless highly correlated. As can be seen, both the Pearson product moment and Spearman rank-order coefficients are on the order of 0.9 between Models "A" and "B," and even the "B" and "AW" formulations correlate at about 0.76. These high intra-model correlations are important because, as we shall see in the next section, the inter-model correlations are substantially lower. Given the findings in Table 8, it seems unlikely that the inter-model differences are attributable simply or only to FREG model specification.

We turn finally to the summary statistics of the (model "B") FREG efficiency scores computed, as in Table 5 above for the DEA model, for each of the annual cross-sectional runs as well as for the pooled estimate conditioned on each year of the analysis; see Table 9. These results show a slight decrease in efficiency for both the cross-sectional and panel FREG models. In the case of the cross-section, mean efficiency decreased from approximately 90 percent in 1982 to around 84 percent in 1993. The FREG panel estimates for individual years show that efficiency decreased from around 88 percent in 1982 to about 84 percent in 1993. Though not especially precipitous, the decline in these efficiency scores is nonetheless noteworthy, and difficult to explain. One aspect that should be pointed out is that the coefficient of variation tends to rise over time, suggesting perhaps that declining efficiency is more marked in subgroups of particular hospitals rather than a pervasive feature of the entire panel. Another is that the pooled estimates, which of course implicitly assume that the average technology prevailing over the period applies to each data point, show greater stability, and perhaps should be characterized as unchanged rather than declining. The correlations between the stacked cross-

Table 9
Summary Statistics, FREG Efficiency Scores,
All Panel Hospitals, 1982-1993

Year/Sample Partition		N	Mean Score	Standard Deviation
1982	Cross-section	186	.8962	.0445
	Pooled	186	.8771	.0723
1983	Cross-section	186	NR	NR
	Pooled	186	.8651	.0683
1984	Cross-section	186	.8977	.0446
	Pooled	186	.8523	.0781
1985	Cross-section	186	.9027	.0398
	Pooled	186	.8353	.1041
1986	Cross-section	186	.8749	.0678
	Pooled	186	.8318	.0830
1987	Cross-section	186	.8306	.1134
	Pooled	186	.8244	.1024
1988	Cross-section	186	.9196	.0244
	Pooled	186	.8365	.0889
1989	Cross-section	186	.7811	.1686
	Pooled	186	.8117	.1316
1990	Cross-section	186	.8421	.0974
	Pooled	186	.8313	.0923
1991	Cross-section	186	.8161	.1340
	Pooled	186	.8238	.1003
1992	Cross-section	186	.8724	.0715
	Pooled	186	.8346	.0836
1993	Cross-section	186	.8388	.1131
	Pooled	186	.8399	.0865
Pooled All Years		2232	.8387	.0938

NR = No Results, no estimate for the frontier regression model.

sections and the pooled values, nonetheless, are quite high, viz., on the order of 0.80 for both the Pearson and Spearman coefficients.

Comparison of DEA and FREG Efficiency Scores

Previous sections have set out the separate results for the DEA and Frontier Regression analyses, and here we compare those findings. Figure 8 shows the pooled results for both the DEA and FREG models. This clearly shows that for the pooled method at this level of analysis the results are similar, though the DEA model produced more of an increase in inefficiency over time than did the FREG model. It is also noteworthy that the DEA scores were actually higher than the FREG scores in 1982, and then began to decline, so that in every year from 1983 through 1993 the DEA pooled scores were lower than the FREG scores. Other than this difference in absolute magnitude, the forms of the lines are very similar.

Figure 9 compares the cross-sectional results for the DEA and FREG models over the study period. As indicated above, there is a slight increase in inefficiency for the FREG model (from ten percent in 1982 to 16 percent in 1993), but a very slight *decrease* in inefficiency for the DEA model from six percent in 1982 to three percent in 1993. The cross-sectional FREG analysis also shows great variability in the scores compared to the FREG panel results and both DEA results. As noted above, this is probably the result of the large number of parameters in the FREG model relative to the smaller number of observations in each of the annual cross-sections. It is also noteworthy that the FREG scores in the cross-section are consistently lower than the DEA cross-section scores, which is the opposite of the findings for the pooled data (except in 1982). The fact that the pooled DEA scores began at a higher absolute level of efficiency than the pooled FREG scores, before switching positions in 1993, and that the cross-sections produced consistently higher scores for the DEA method, lends credence to the idea that the decline in pooled DEA scores over time is a methodological artifact.

Table 10 presents both Pearson and Spearman correlation coefficients between the cross-sectional DEA and frontier regression efficiency scores for panel hospitals. The Pearsonian correlation between the scores ranged from a low of .118 in 1992 to a high of .394 in 1987. There was no discernible pattern in terms of increasing or decreasing correlation coefficients over time. The Spearman rank-order coefficient ranged from a low of .157 in 1992 to a high of.373 in 1987, showing the same pattern as the Pearsonian product moment values. Once again, there was no discernible increase or decrease in correlation between the results yielded by either method over time. Thus, each of the correlation measures show consistent results, with a low to moderate correlation between the cross-sectional inefficiency scores.

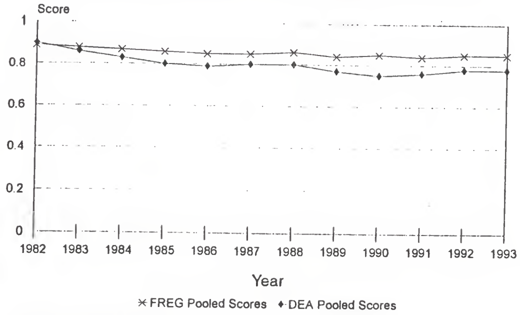
Analysis of Efficiency Correlates and Concordance

Preliminaries

The preceding section shows that the DEA and FREG models produce results that correlate reasonably well at the level of the industry, but

Figure 8

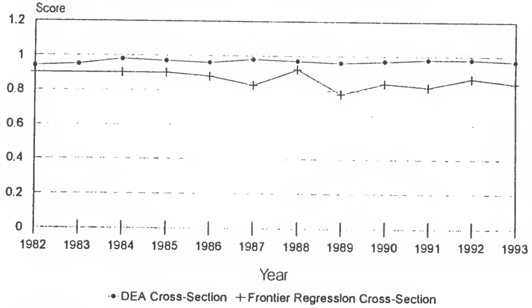
Pooled Mean DEA and Regression Scores



Inverse of Regression Score

Figure 9

Cross-Section DEA and Regression



Inverse of Regression Score

Table 10
Correlation Coefficients, DEA and FREG Efficiency Scores,
All Panel Hospitals, 1982-1993

Year/ Sample Partition	Pearson Coefficient (Rho)	Spearman Coefficient (Rho)
1982 Cross-section	0.2511 (0.0005)	0.2865 (0.0001)
1983 Cross-section	NR	NR
1984 Cross-section	0.1397 (0.0571)	0.1907 (0.0091)
1985 Cross-section	0.2998 (0.0001)	0.2800 (0.0001)
1986 Cross-section	0.1415 (0.0540)	0.2538 (0.0005)
1987 Cross-section	0.3937 (0.0001)	0.3730 (0.0001)
1988 Cross-section	0.2862 (0.0001)	0.3054 (0.0001)
1989 Cross-section	0.1635 (0.0258)	0.1819 (0.0130)
1990 Cross-section	0.3746 (0.0001)	0.2267 (0.0019)
1991 Cross-section	0.2978 (0.0001)	0.2946 (0.0001)
1992 Cross-section	0.1176 (0.1098)	0.1568 (0.0325)
1993 Cross-section	0.3789 (0.0001)	0.2320 (0.0014)
Pooled All Years	0.2668 (0.0001)	0.3147 (0.0001)

NR = No Results, no estimate for the frontier regression model.

not nearly as well at the level of individual hospital observations. Although we have already described why such discrepancies might be expected, the absence of broad agreement between the DEA and FREG scores nonetheless raises the question of which model produces more "believable" or "usable" results. Whether the efficiency differences detected by either model are valid must be appraised before this question can be answered with any degree of confidence. The major objective of the second-stage analysis reported in this section is to provide some basis for drawing conclusions about the construct validity of the two models and, thereby, criteria for selecting between them.

The point of departure for this work is the construction of multivariate statistical models designed to account for observed variations in efficiency scores by means of a common set of predictor variables or correlates, i.e., to estimate regression models of the following general form:

$$S_{ijt} = f(Y_{it};\ B^*, u_{it}) \tag{8}$$

where S_{ijt} is the efficiency score for the *ith* observation, *jth* DEA/FREG specification, and *tth* time point, Y_{it} is the vector of predictor variables, and B^* and u_{it} are, respectively, the parameter vector and error variance to be estimated.

The broad logic of this approach may be justified first by recalling that the DEA/FREG estimates simply gauge the efficiency of observed input-output relationships; they are not necessarily designed to provide an explanation of why efficiency is either relatively high or low. Second-stage explanatory models of efficiency scores not only shed light on this question, but they also provide an indirect means of testing the construct validity of the FREG and DEA models. Consider the common assumption in the literature that proprietary hospitals use resources more efficiently than non-profits do. All else equal, an indicator variable for proprietary hospitals would thus be expected to be a significant predictor of the level of observed efficiency. If that indicator variable is actually found to be significantly positive in a multivariate model of efficiency scores, *prima facie* evidence favoring the validity of the model generating that score is adduced. If the indicator is statistically insignificant or negative, questions about the degree to which the model actually taps efficiency outcomes may surface. This approach is hardly foolproof, but if there are a sufficient number of useful and non-controversial predictors, then the multivariate analyses help confirm whether inefficiency has been appropriately indexed by either or both models. If one model tends consistently to confirm expectations, while the other does not, there may be grounds for according more weight to one set of findings than the other.

Predictor Variables

Managerial responses or practices likely to contribute to variations in efficiency levels across hospitals and time may be grouped into

two broad categories: 1) those stemming from internal claims on resource allocations by the medical staff, the governing board and other competing groups inside the institution, and 2) those driven by competitive pressures from the external market. The explanatory variables for the multivariate model formulated in this section attempt to represent these internal and external forces as realistically as possible within the constraints of available data. While, as before, detailed descriptions of each of these variables are presented in the glossary in Appendix Table A.1, they may be briefly described here as follows.

First, like countless other studies, we use hospital control or ownership to reflect variations in management aims and philosophy. A fivefold vector of dummy variables is constructed for each year encompassed by the analysis, comprised of two categories of proprietary hospitals (facilities owned by corporations and others owned by only one or two individual investors); two categories of non-profit institutions (community or voluntary hospitals and those operated by religious groups) and the residual category of facilities owned and operated by governmental units at all levels. A dummy variable taking the value of one if the hospital changed ownership or control in a given year is also constructed. This variable assumes for convenience that what impact that change in ownership or control has on efficiency is captured without a time lag. Because managerial practice is surely more difficult or problematic in larger, more complex facilities and/or those with a larger and more varied medical staff, we incorporate indicators of each (cf., Alexander and Morrisey, 1992; Custer 1992; Jenson and Morrisey, 1986). We introduce size dummies measured in terms of the total number of beds as well as an index of the number of different medical specialties represented in the pool of physicians with privileges at the facility; see Appendix Table A.1.

In addition to these measures, we construct three variables characterizing managerial efficiency practices more directly. One gauges whether the hospital engages in a philanthropic wage policy for its (non-physician) work force, i.e., whether wage payments are higher than would otherwise be dictated by conditions in the local labor market for hospital workers.[10] Using the local market delineations described earlier, wage dummies are constructed that indicate whether the mean wages paid by a given hospital for different types of personnel differ from the averages prevailing in its local market. If mean wages in each labor category are higher than the average prevailing in the local (primary) market in a given year, a value of one is assigned to the

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[10] See, among others, Sloan and Steinwald (1980) and Feldstein (1971) for discussions of the philantrophic wage hypothesis; also see Robinson (1989). Although this issue might have been handled directly in the estimation by replacing hospital-specific wage rates with local market average wages, the procedure would complicate the interpretation of the results, especially the DEA results. We did, however, build this issue into the second stage of the analysis on efficiency correlates below.

category labelled above-average; similarly, if mean wages are below the local average, a value of one is assigned to the below-average dummy. All other facilities, including hospitals in primary monopoly markets, comprise the omitted or reference category for this dummy vector. If the estimated coefficient on the above-average dummy is significantly positive, or if the coefficient on the below-average variable is significantly negative, a plausible argument can be made for *efficiency-adjusted* wages; the opposing pair of coefficients would of course imply that philanthropic wage determination cannot be ruled out.

Management practices bearing on productive efficiency may also be reflected in decisions concerning investment and revenue-generating activities. In many industries, additions to total capital stock may be a primary indicator of the efficiency goals of management. In the hospital industry, however, capital augmentation may simply be the outcome of internal pressures by competing constituencies. Yet, in either case, one might expect net investment to be correlated with the efficiency level of the facility. We include a (dollar) measure of annual net investment with this expectation in mind. To ensure that the effect of the net investment variable is measured precisely, we also introduce a vector of dummy variables characterizing the scope or mix of specific services offered by a given hospital relative to others in its local market.[11] Hospitals offering a greater service mix than the local average are treated as technological leaders, and they are assigned a value of one on the above-average service mix dummy, zero otherwise. Hospitals offering a below-average mix of services are characterized in opposing terms. The general expectation is that technological leadership is purchased at the cost of somewhat greater inefficiency, all else equal. In a similar vein, the ability to manage resources efficiently may be systematically related to the scope of operations and revenue-producing activities. We use the percentage of total revenues derived from patient care centers or, inversely, the fraction of revenues attributable to non-patient care pursuits, as a proxy of this management condition. The maintained hypothesis is that the more exclusively revenue generation is tied to patient care activities, the higher the efficiency level of the institution.

Efficiency levels are also expected to be influenced by external pressures arising from competition in the local health care marketplace. Theoretically, this pressure should serve to induce managers to be more efficient, so that more competitive markets have higher mean levels of efficiency, and vice versa. However, these pressures may have the opposite effect in the hospital industry, because more competitive markets are likely to foster non-price competition, which lowers efficiency levels (Chirikos, 1992; Dranove et al., 1993; Robinson and

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[11] This dummy vector also proxies case mix and thus provides an indirect control for case mix variations on efficiency scores. The case mix measure (Appendix Table A.1) is not introduced explicitly in the explanatory models set out in this section because it is embedded in the output variables used to estimate the FREG and DEA models.

Luft, 1985; and Weisbrod, 1991). In either case, the relationship between competitive pressure and efficiency scores must be taken into account in the multivariate analysis. Because recent developments in local hospital markets have multiplied the number and type of potential competitors (managed care, substitute ambulatory facilities, physician groups, etc.) we concluded that a conventional Herfindahl index (or related concentration measure) would not adequately serve this purpose (Chirikos and White, 1987). Introducing a more extensive set of competition indicators directly into the model, however, created some problems in preliminary work.

For this reason, a summary index was created (instrumented) from an auxiliary equation. Since, in principle, market share should be increasingly smaller as the degree of competitiveness of the local health care market increases, this equation uses the weighted market share of each hospital in its three largest markets as the dependent variable; see Appendix Table A.1. The regressor set includes a dummy vector for the number of hospital competitors, the per capita supply of physicians, the pace of HMO and alternative delivery system development, and the number of nursing home beds in the primary market; it also includes selected demographic and economic characteristics of the local area.[12] Results from the estimation of this model are presented in Appendix Table A.4. The linear combination of the OLS parameters and the values of the regressors for each of the observations in the data set are then used to index the degree of competitiveness in the local market in each year of the analysis. If greater efficiency is stimulated by more competition, the estimated coefficient on this (endogenous) market share variable should be significantly negative.

Model Specification and Estimation

To recap briefly, a set of predictor variables representing internal and external factors expected to influence efficiency levels is constructed for the purpose of estimating multivariate regression models that, amor~ other things, cast light on the construct validity of the DEA and FREG models. We begin with multivariate models that use the estimated FREG and DEA efficiency scores as dependent variables and this (RHS) set of predictor variables. (A subsequent subsection sets out the results of models that use slightly different dependent variables). Since panel data were used to estimate the DEA and FREG efficiency models and the resulting efficiency scores thus refer to repeated observations on the same set of Florida hospitals over the period 1982-1993, these regression models are most usefully specified in longitudinal or panel terms as well, i.e., with the value of each observation differing by both hospital unit and time points.

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[12] Because many of these socioeconomic characteristics and the hospital market area definitions themselves are highly correlated with the degree of urbanization of the local area, we do not introduce a separate urban/rural variable directly into this model.

Such a specification has a crucial advantage here because it permits the impact of omitted factors that may be unique to particular hospitals (or time periods) to be taken into account. The analysis of panel data now typically models this unobserved heterogeneity as either *fixed* or *random* effects (Hsiao, 1992). In the first case, indicator variables for each and every observation (or time period) are, in effect, introduced into an OLS regression, thus directly factoring out any systematic (fixed) influence of individual observations with respect to unmeasured or omitted factors in the explanatory model. In the second case, these individual effects are assumed to be randomly distributed, and the error term is treated as having two parts, one unique to each observational unit and the other having the characteristics of the classical random disturbance. Efficient estimation of this error or variance component model is yielded by means of Generalized Least Squares (GLS), a two-step procedure that uses the variances estimated from an OLS regression to transform the variables, and these transformed variables to estimate the regression equation. Test statistics are available to help sort out whether the fixed or random effects model is best suited to a particular estimation. Since these test statistics consistently supported the random effects GLE estimator, only these results are presented in the next subsection.

Two additional matters relating to the modeling strategy here warrant brief comment. One is that preliminary work tested the panel models not only for individual (hospital-specific) effects but also for temporal effects, i.e., two-way models. These two-way estimates varied somewhat from their one-way counterparts, but only slightly. In general terms, they tended to add marginally to the overall explanatory power of the statistical models, but the parameter estimates were quite similar to those yielded by the one-way version of the estimating model. Since temporal effects here may be interpreted as unobserved heterogeneity arising from changing policy regimes at the state and federal levels, these findings may be of more than passing interest. More detailed consideration of temporal changes, however, is left for future work.

A related modeling issue is potential bias arising from autoregressive efficiency scores. As it happens, the year to year correlation between efficiency measures is not great. Pearson coefficients for lagged values of FREG cross-sectional scores, for example, are generally on the order of 0.4-0.5, and never exceed 0.7. Nonetheless, in preliminary work, we estimated autoregressive versions of the panel models to assess the influence of efficiency "habits." These autoregressive models never fit the data very well and, hence, are not reported here.

Regression Results

Tables 11 and 12 present regression coefficients, test and summary statistics for the random effects models estimated for panel and cross-sectional efficiency scores from the FREG and DEA models above. Table 11 is considered first in some detail as a means of elucidating the aims and results of this second-stage of the analysis. It shows the effects

Table 11
Regression Estimates, Random Effects Models of FREG and DEA Efficiency Scores, Final Panel Specification,[a] All Hospitals, 1982-1993

Explanatory Variables[b]	Means (Std. Dev.)	GLE Coefficients (Absolute t-ratios) FREG Scores	DEA Scores
Control: Religious (=1)	0.074	-0.0112	-0.0471
	(0.262)	(0.78)	(2.27)
Proprietary Corporation (=1)	0.376	0.0039	0.0187
	(0.485)	(0.50)	(1.59)
Other Proprietary (=1)	0.034	0.0341	0.0024
	(0.183)	(2.72)	(0.12)
Government (=1)	0.168	0.0415	0.0307
	(0.374)	(5.02)	(2.36)
Ownership Change (=1)	0.051	-0.0217	0.0155
	(0.220)	(3.00)	(1.29)
Beds: 100 or Fewer (=1)	0.218	-0.0189	0.0233
	(0.413)	(2.17)	(1.74)
300 or More (=1)	0.324	0.0129	-0.0055
	(0.468)	(1.60)	(0.45)
Physician Staff Mix (Index/100)	0.194	-0.0024	-0.3504
	(0.072)	(0.06)	(4.96)
Wage Rates: Above Local Average (=1)	0.224	0.0337	-0.0104
	(0.417)	(7.66)	(1.43)
Below Local Average (=1)	0.234	-0.0361	0.0014
	(0.423)	(8.23)	(0.19)
Net Annual Investment ($ Millions)	3.965	-0.0009	-0.0019
	(8.094)	(3.93)	(5.23)
Service Mix: Above Local Average (=1)	0.141	0.0083	0.0161
	(0.348)	(1.08)	(1.32)
Below Local Average (=1)	0.108	0.0013	0.0014
	(0.310)	(0.17)	(0.11)
Patient Care Revenue Ratio	0.968	0.2071	0.1696
	(0.048)	(3.59)	(1.84)
Market Share (Endogenous Percent)	0.236	0.0874	0.4256
	(0.178)	(3.36)	(1.19)
Constant	-	0.6118	0.6897
		(10.75)	(7.60)
N	2,232	2,232	2,232
Efficiency Score: Mean	-	0.839	0.801
Standard Deviation	-	0.094	0.148
Lagrange Multiplier Test	-	1856.15	925.14
Hausman Test	-	0.000	0.000
R-squared	-	0.096	0.145

a. See text for a description of alternative model specifications.

b. See Appendix Table A.1 for variable definitions and data sources.

Table 12
Selected Regression Estimates, Random Effects Models of FREG and DEA Efficiency Scores, Final Cross-Sectional Specification,[a] All Hospitals, 1982-1993

Selected Variables[b]	GLE Coefficients (Absolute t-ratios)	
	FREG Scores	DEA Scores
Control: Religious (=1)	0.0012	-0.0332
	(0.08)	(3.42)
Proprietary Corporation (=1)	0.0162	0.0090
	(2.00)	(1.57)
Other Proprietary (=1)	0.0073	0.0148
	(0.52)	(1.41)
Government (=1)	0.0325	0.0115
	(3.59)	(1.73)
Beds: 100 or Fewer (=1)	-0.0227	0.0031
	(2.44)	(0.46)
300 or More (=1)	0.0162	0.0084
	(1.92)	(1.40)
Wage Rates: Above Local Average (=1)	0.0292	-0.0018
	(5.68)	(0.44)
Below Local Average (=1)	-0.0405	0.0107
	(7.91)	(2.71)
Net Annual Investment ($ Millions)	-0.0006	0.0004
	(2.26)	(1.89)
N	2,232	2,232

a. See Appendix Table A.5 for complete estimating equations and summary statistics; also see the text for a discussion of alternative model specifications.

b. See Appendix Table A.1 for variable definitions.

of the predictor variables on the panel estimates of the efficiency scores derived from the final DEA and FREG models estimated on the full panel data set of 186 hospitals across 12 years, i.e., 2232 observations. As may be recalled, and as is presented near the bottom of Table 10, the mean efficiency scores from this specification are fairly close to one another, though the standard deviation of the DEA score is somewhat higher than its FREG counterpart. The bottom rows also show, incidentally, that the random effects (GLE) model specification for these data is quite appropriate on the basis of two important specification tests: the Lagrange Multiplier test decisively rejects excluding individual hospital effects in the model, whereas the Hausman statistic rules out, again quite decisively, specifying these individual effects as fixed rather than a random component of the error term. Interestingly, the DEA model fits the data marginally better as evidenced by the R-squared value, though it is important to note that the GLE estimator always affects the coefficient of determination so this difference must be interpreted cautiously.

In view of these summary and test statistics, it is quite interesting that the two models yield a number of distinctly different results. While each model provides weak evidence that efficiency levels differ significantly by hospital control, the net control-efficiency relationship differs between the DEA and FREG estimates. On the one hand, the FREG results suggest that facilities owned and operated by religious groups and corporate investors do not differ from the (omitted) voluntary, not-for-profit category, while other proprietaries (single owner and partnerships) and governmental units do differ, in both cases in highly significant terms. The model estimated on the DEA scores provides similar results for government hospitals, but differs in regard to the others. This model fails to find a significant net effect on the other proprietary category and, curiously, it now detects a weak positive coefficient on the corporate proprietary variable. Whether these specific findings imply that only selected dimensions of efficiency are tapped in common by each model, such as the efficiency configuration of governmental hospitals, is unclear.

The two models exhibit similarly mixed coefficients on the other regressor variables as well. The FREG model shows, for instance, that the efficiency level of facilities experiencing a change in ownership/control in a given year is significantly lower than organizations keeping the same owner, whereas the DEA version does not. The effects of size on efficiency levels also differ between the two sets of results. The model based on the FREG efficiency scores provides reasonable evidence that size matters, and in the direction expected if hospital production is subject to scale economies, i.e., smaller facilities (100 or fewer beds) have significantly lower efficiency scores than middle-size organizations (101-299 beds), while larger hospitals (300 or more beds) have higher scores than this same reference group, all else equal. The DEA model, by contrast, suggests only tenuous effects of size, and in the opposing direction.

Equally divergent results are encountered in the estimated coefficients on the physician staff, philanthropic wage dummies and market share variables. In the first case, the FREG model fails to detect any influence of the size and composition of the physician staff, whereas the DEA model detects a highly significant negative impact, as predicted. In contrast, the FREG estimates imply that hospitals pay the marginal value product of labor or, put differently, that relative wage payments in a given market are likely to be efficiency-adjusted. (cf., Zuckerman et al., 1994). The DEA estimates provide weak evidence in favor of the philanthropic wage setting hypothesis, though the negative coefficient on the above-average wage dummy narrowly misses statistical significance at conventional levels. However, the DEA-related model fails to find any significant influence of local competitive pressures, while the FREG model supports the notion that competitive dynamics in the hospital industry *reduce* efficiency, i.e., that the efficiency level increases as the adjusted market share (and by implication the degree of concentration in the local market) increases. In interpreting this finding, recall that competition is modeled not only with respect to other hospitals in the local market but also with respect to HMO penetration and the development of alternative service delivery mechanisms in those markets.

Yet, several predictors perform comparably across the FREG and DEA-related specifications. Both models find that net investment and efficiency are inversely related; similarly, both suggest that hospitals engaged in non-patient care revenue-producing activities tend to be more inefficient, all other things equal. While this specific result may stem from the fact that only patient care-related outputs are accounted for in the FREG and DEA efficiency scoring, it is nonetheless reassuring to note that each model tends to treat that fact equivalently. Finally, neither model finds any influence of the service mix of the hospital relative to its local competitors.

Explanatory models using stacked efficiency scores derived from the 12 annual cross-sectional models produce similarly disparate findings. Selected estimates are presented in Table 12; the complete estimating equations and test statistics are set out in Appendix Table A.5. Such cross-sectional results might be expected to differ somewhat, and they do. As can be seen, the net effects of the control variables are quite different, with each model now detecting an efficiency advantage for proprietary corporations, and the DEA results also detecting such an advantage for other proprietary and a net disadvantage for hospitals run by religious groups. Unaccountably, the impact of net investment on the cross-section in the DEA model is now positive. Though in many cases measured less precisely, the coefficients on the remaining variables in the cross-sectional runs are similar to the panel estimates in Table 11 above.

In view of these disparate findings, several additional sensitivity tests of the explanatory models were carried out. In order to test for possible measurement bias, explanatory models using panel FREG and DEA scores derived from cost data *unadjusted* for temporal changes in the

hospital input price index were estimated; see the section on variable construction above. Even though no dramatic differences were detected in the FREG efficiency estimates, the issue of the appropriate functional specification of the translog model led us to estimate explanatory models for the alternative FREG specification (Model A) as well. Appendix Table A.6 presents some of the results of these sensitivity tests. It shows signs, magnitudes and statistical significance of the explanatory variables remarkably similar to those set out in the counterpart estimates in Table 11 above. The only noteworthy exceptions are selected differences in the estimated coefficients on the hospital control dummies in the DEA model. This suggests that minor changes in specification or measurement are not likely to alter the main results to any significant degree. In particular, differences between the FREG and DEA results arising simply from the choice of functional form for the FREG model can, as a result, be ruled out.

There is, however, another issue relating to FREG specification that may be even more important in the present context, viz., whether the model is indeed separable into two parts, one estimating the efficiency score and the other estimating the parameters of the explanatory model. Generally speaking, this two-stage approach may impart bias if the error terms across the two FREG-related equations are correlated to any significant degree. It bears repeating that the two-stage approach was adopted primarily because categorical explanatory variables cannot be directly introduced into the DEA model and we are most interested in comparing the two models. Yet, given the disparate findings between the DEA and FREG models, testing whether the FREG specification produces such bias seemed warranted. For this reason, we reestimated the Model A and Model B variants the FREG translog model (see the model specification section above), adding the set of explanatory variables (Table 11) to the regressor vectors of outputs and factor prices. The estimated subsets of coefficients on the explanatory variables are abstracted in Table 13; the complete set of results for all regressor variables are presented in Appendix Table A.7 below.

The results in Table 13 are quite consistent with the FREG findings in Tables 11-12 above, so correlated errors across FREG equations are not likely to impart substantial bias to the two-stage explanatory models of efficiency correlates. In examining the estimates in Table 13, recall that the dependent variable in the FREG translog model is the logarithm of total costs. Coefficients in this model should, all things equal, be opposite in sign to those set out in Tables 11 and 12. As can be seen, this general expectation is met, with only two exceptions. Column 1 shows, for example, that the net effects of ownership changes, physician staffing, wage policy, net annual investments, revenue policy and local market competition are opposite in sign to the coefficients in Table 11 as well as statistically significant at conventional levels. Since these consistent FREG findings also find considerable support in the literature, it seems unlikely that they are either perverse or artifactual. The effects of local service scope are again shown to be insignificant regressors, though it is unclear whether this similarity has any real meaning. However, as before, some differences are detected

Table 13
Frontier Regression Estimates of Efficiency Correlates,[a]
Various Specifications, 1982-1993

Selected Variables[b]	MLE Coefficients (Absolute t-ratios) Cost Model B	Cost Model A
Control: Religious (=1)	-0.0010	-0.0106
	(0.69)	(0.76)
Proprietary Corporation (=1)	-0.0287	-0.0349
	3.19)	(3.80)
Other Proprietary (=1)	-0.0116	-0.0061
	(0.56)	(0.28)
Government (=1)	-0.0774	-0.0844
	(6.45)	(7.37)
Ownership Change (=1)	0.0316	0.0214
	(2.20)	(1.41)
Beds: 100 or Fewer (=1)	-0.0837	-0.0841
	(5.78)	(5.99)
300 or More (=1)	0.0599	0.0495
	(4.35)	(3.67)
Physician Staff Mix (Index/100)	0.6070	0.6863
	(8.20)	(8.89)
Wage Rates: Above Local Average (=1)	-0.0622	-0.0194
	(6.92)	(2.00)
Below Local Average (=1)	0.0480	0.0074
	(5.62)	(0.81)
Net Annual Investment ($ Millions)	0.0029	0.0028
	(7.56)	(7.29)
Service Mix: Above Local Average (=1)	-0.0086	-0.0107
	(0.64)	(0.88)
Below Local Average (=1)	0.0190	0.0127
	(1.50)	(0.97)
Patient Care Revenue Ratio	-0.4429	-0.5526
	(6.07)	(8.30)
Market Share (Endogenous Percent)	-0.1358	-0.1940
	(6.02)	(8.44)
N	2,232	2,232

a. See text for a description of alternative model specifications and Appendix Table A.7 the complete estimating equations and test statistics.

b. See Appendix Table A.1 for variable definitions and data sources.

in regard to control and hospital size. While all versions of the FREG model suggest significant cost (efficiency) advantage for government hospitals over their voluntary counterparts, the results relating to proprietaries differ from those derived from the two-stage model above. There is little basis for understanding why these different results arise. The differences in the net effects of size may be attributable simply to the pronounced influence of cost levels in very large institutions. While these effects are later factored out in the conditional expectations used to compute the efficiency scores, they bear directly on the cost variables used in computing the frontier.

The right-most column of Table 13 shows markedly similar results for the FREG specification that includes a large number of cross-product and interaction terms. As can be seen, despite the substantial increase in the number of regressors, the net effects of all but one of the explanatory variables are quite similar to those in Column 1; cf., the full results in Appendix Table A.7. The exceptional case is the precision of the estimated coefficient on the "below average" philantrophic wage category, a result perhaps of the wage cross-product terms in this variant of the FREG model. The remaining coefficients provide reasonably convincing evidence that the explanatory variable set is robust to specification and, thereby, that it provides a plausible point of departure in appraising the validity of the FREG and DEA efficiency models.

Ancillary Models of Concordance

In order to cast additional light on the factors that are associated with differences between the parametric and nonparametric results, we extended the analysis of efficiency correlates to encompass several ancillary models. The first step here involved merging the efficiency scores from the FREG and DEA estimation, defining new dependent variables by delineating overlapping subsamples from each vector of scores, and then reestimating the explanatory models. To illustrate, we delineated subsamples of highly efficient (inefficient) hospitals by selecting observations in the highest (lowest) quartile of *both* vectors of scores in the *same* year; we also delineated overlapping subsamples one standard deviation above (below) each of the respective means during the same year. These subsamples were then used to create dichotomous dependent variables, and new versions of the explanatory model were specified and then estimated by appropriate maximum likelihood (Probit) methods.

Unfortunately, this modelling effort did not produce many usable results, and it is not reported here. The descriptive data set out in Table 14 provide some reasons for these poor results. The top panel shows the number of hospitals identified as highly efficient (inefficient) by *both* models in the *same* year is unusually small when highly efficient (inefficient) is defined as having a score in the top (bottom) quartile of each vector in the same year. Even when the median is used as the cut point, the overlapping samples tend to be quite small as the bottom panel indicates. The descriptive characteristics of the

Table 14
Selected Characteristics of Hospitals Classified
By Different Efficiency Scoring Methods, 1982-1993

Scoring Criteria/ Characteristics[a]	Mean Number or Proportion					
	Overlapping Samples		FREG Scores Only		DEA Scores Only	
	Efficient	Inefficient	Efficient	Inefficient	Efficient	Inefficient
Top vs Bottom Quartiles						
Admissions	6855	8494	8536	6900	5987	10658
Length of Stay	6.1	6.9	6.3	6.8	6.3	6.8
Beds	211	331	261	269	200	381
Occupancy	55.8	52.6	57.8	51.5	53.2	55.8
FTEs per 100 Cases	7.5	11.7	7.7	10.9	8.6	10.6
Cost per Case	3696	7309	4043	6504	4598	6557
N	227	217	558	558	558	558
Above vs Below Median						
Admissions	7589	8601	8646	7890	6942	9630
Length of Stay	6.3	6.7	6.4	6.7	6.4	6.7
Beds	234	303	276	287	227	336
Occupancy	57.5	55.0	57.7	53.0	55.1	56.4
FTEs per 100 Cases	7.8	9.7	8.1	10.1	8.5	9.7
Cost per Case	4034	5733	4463	5948	4618	5795
N	693	1539	1116	1116	1115	1117

a. See text for a discussion of efficiency scoring and distribution cut points.

subsamples in Table 14 provide some clues about the factors contributing to the divergence in scores. Note, for instance, the difference in the mean number of beds in the top quartile hospitals identified by the FREG model relative to its counterpart group in the DEA model.

As a result, ancillary models were then formulated to account for the *differences* between the FREG and DEA scores more directly. We subtracted the FREG score from the corresponding DEA score and, initially, created a dummy variable taking the value of one if this difference was positive, zero otherwise. Given the results obtained when the explanatory variable set was introduced directly into the FREG estimation, we had the opportunity to look at the differences in scores with and without this "adjustment" for the covariates. Since the mean of the "adjusted" FREG efficiency scores was now higher, the fraction of the observations assigned a value of one decreased. Accordingly, we created a variant of the dependent variable, with the difference between the DEA and adjusted FREG scores scaled to roughly the difference between the means of the two efficiency score distributions, i.e., -0.05 percentage points. These three versions of the "difference" between the scores were then used as dependent variables in Probit versions of the explanatory model. In effect, these Probit models are designed to gauge the factors responsible for driving the FREG and DEA scores either closer together or farther apart. Table 15 presents the results of this estimation.

Many of the explanatory variables are highly significant, though opposite in sign, to the corresponding parameter estimates in Tables 11-12 above. Interestingly, the pattern of these coefficients is similar, irrespective of whether the score difference is computed with the unadjusted or adjusted FREG scores. Since the adjusted FREG score controls for the net effect of the explanatory variables, attributing their influence here entirely to the DEA results, the failure to observe a dramatic change in the pattern of results lends indirect support for the simpler models set out in Tables 11-12. As such, these results provide important clues about the divergent results of the FREG and DEA models.

Consider, for example, the bed (size) dummies. The FREG scores reported above were consistently lower for small facilities and higher for larger ones, while the less consistent DEA pattern generally tended to the opposite conclusion. Table 15 shows that the likelihood a small institution will be treated as "more" efficient by the DEA model than the FREG model is significantly and consistently positive across the three versions of the Probit model. This probability is similarly and consistently negative for larger facilities, though the coefficients are measured with slightly less precision in the first and second columns, as evidenced by the t-ratios. Nonetheless, the pattern of these findings imply that the divergent DEA-FREG results are partially attributable to the size distribution of the sample data, and that the scores might be closer together were the analysis restricted to size-stratified models. We return to this point momentarily.

Table 15
Regression Estimates, Probit Models of Difference in
FREG and DEA Efficiency Scores,[a] Various Specifications, 1982-1993

Explanatory Variables[b]	Probit Coefficients (Absolute t-ratios)		
	DEA-Unadjusted FREG > 1 (=1)	DEA-Adjusted FREG > 1 (=1)	DEA-Adjusted FREG > -0.05 (=1)
Control: Religious (=1)	-0.5164	-0.4893	-0.5566
	(4.00)	(3.74)	(4.40)
Proprietary Corporation (=1)	0.0940	0.1030	0.2127
	(1.30)	(1.42)	(2.95)
Other Proprietary (=1)	0.2081	0.1154	0.1433
	(1.32)	(0.72)	(0.91)
Government (=1)	-0.1900	-0.1215	0.0254
	(1.99)	(1.27)	(0.27)
Ownership Change (=1)	0.3482	0.3040	0.1612
	(2.76)	(2.42)	(1.27)
Beds: 100 or Fewer (=1)	0.2521	0.2508	0.1840
	(2.72)	(2.70)	(1.95)
300 or More (=1)	-0.1504	-0.1451	-0.2754
	(1.86)	(1.78)	(3.46)
Physician Staff Mix (Index/100)	-4.0109	-3.9657	-4.2662
	(6.44)	(6.35)	(6.84)
Wage Rates: Above Local Average (=1)	-0.2336	-0.1063	-0.1675
	(3.14)	(1.43)	(2.31)
Below Local Average (=1)	0.2543	0.0975	0.1031
	(3.60)	(1.36)	(1.46)
Net Annual Investment ($ Millions)	-0.0057	-0.0118	-0.0119
	(1.35)	(2.68)	(2.74)
Service Mix: Above Local Average (=1)	0.0911	0.1569	0.2835
	(0.95)	(1.61)	(3.00)
Below Local Average (=1)	-0.0674	-0.0982	-0.1549
	(0.70)	(1.01)	(1.62)
Patient Care Revenue Ratio	-0.3975	-0.5089	0.2207
	(0.55)	(0.70)	(0.30)
Market Share (Endogenous Percent)	-0.1[illegible]03	0.1637	0.0159
	(1.04)	(0.89)	(0.09)
Constant	0.9187	0.8870	0.5263
	(1.30)	(1.25)	(0.74)
N	2,232	2,232	2,232
Dependent Variable: Mean	0.392	0.370	0.460
Standard Deviation	0.488	0.483	0.498
Model Chi-Squared	288.33	286.29	333.32

a. See text for a description of alternative model specifications.

b. See Appendix Table A.1 for variable definitions and data sources.

Table 15 also suggests that the inconsistent pattern of estimated coefficients on the hospital ownership dummies stems from systematic differences in the DEA and FREG estimations. Note, for example, that the DEA scoring is significantly less likely than the FREG model to treat religiously-affiliated hospitals as more highly efficient, whereas there is weak, mixed evidence suggesting that it more likely to treat proprietaries that way. There is also mixed evidence in respect to the government hospitals in the sample, though most indications imply that the two models accord reasonably well for these facilities, in contrast to the proprietary sector. The remainder of the regressors provide general support for the inferences about the two models drawn above in Table 11-12.

In view of the mixed findings with respect to ownership and size, we investigated in greater detail the patterns of outputs and inputs in hospitals differing in these specific characteristics. This more narrowly focussed probe was predicated on the hunch that market segmentation would be treated somewhat differently by the parametric and nonparametric models, so if distinct patterns of service deliveries were more directly controlled, the factors contributing to efficiency score differences would be more easily detected. In order to test this proposition in operational terms, we first delineated the patterns of service delivery of the six outputs used in computing the efficiency scores (see the section on variable construction above) in reference to the consistency of their rank orderings. More particularly, if at least five of the six outputs of a given hospital ranked in the top (second, third, lowest) quartiles (later collapsed into above and below the median subgroups) of such rankings in a given year, that institution is treated as having a consistent or nonsegmented pattern of service delivery; and vice versa.

We then investigated whether these patterns of service delivery varied across different types of hospitals. Table 16, for example, cross-classifies the frequencies of hospitals having mixed or consistent (above or below the median) patterns of output delivery by control status. Among others, the substantial difference between expected and observed frequencies of "mixed" or inconsistent output patterns in the proprietary category (here combining both corporate and single-owner subgroups) is quite striking. Since we have already seen in the descriptive analysis above that size also varies by ownership grouping, these findings provide a means of appraising whether output patterns contribute to the difference in efficiency scores between the DEA and FREG models. With this goal in mind, we created a dichotomous variable (ΔQ) taking the value of one if the hospital was judged to have an *inconsistent* pattern of outputs, zero otherwise. This dummy was then introduced into the Probit model of score differences, viz., the model using the DEA *less* adjusted-FREG difference of more than -0.05 (Column 3, Table 15 above), both as a main effect and as interaction effects with the size variables. Selected results of this estimation are presented in Table 17.

Table 16
Expected and Observed Frequencies of Consistent Output Patterns,
By Hospital Control, All Panel Hospitals, 1982-1993

Control		Frequencies			
		Total	Mixed Pattern	Always Above Median	Always Below Median
Religious:	Observed	166	79	60	27
	Expected	166	115.1	23.8	27.1
Voluntary:	Observed	774	495	160	119
	Expected	774	536.8	111	126.2
Proprietary:	Observed	917	769	15	133
	Expected	917	636	131.5	149.5
Government:	Observed	375	205	85	85
	Expected	375	260	53.8	61.2
Total		2,232	1,548	320	364
Chi-Squared (6 df)		263.7			

Table 17
Selected Regression Estimates, Probit Models of Difference in FREG and DEA Efficiency Scores,[a]
Specifications with Output Pattern Variables and Interactions, 1982-1993

Explanatory Variables	Probit Coefficients (Absolute t-ratios)		
	DEA-Adjusted FREG > -0.05 (=1)	DEA-Adjusted FREG > -0.05 (=1)	DEA-Adjusted FREG > -0.05 (=1)
Control: Religious (=1)	-0.5353	-0.5318	-0.5390
	(4.22)	(4.20)	(4.28)
Proprietary Corporation (=1)	0.1999	0.2082	0.2517
	(2.77)	(2.89)	(3.57)
Other Proprietary (=1)	0.1256	0.1247	0.1754
	(0.79)	(0.79)	(1.11)
Government (=1)	0 0382	0.0268	0.0206
	(0.40)	(0.28)	(0.22)
Ownership Change (=1)	0.1668	0.1738	0.1760
	(1.32)	(1.38)	(1.39)
Beds: 100 or Fewer (B_{100} =1)	0.2641	-0.0961	-
	(2.67)	(0.58)	
300 or More (B_{300} =1)	-0.2422	-0.2415	-
	(3.01)	(1.38)	
Inconsistent Output Pattern: ΔQ (=1)	0.2044	0.2847	-
	(2.81)	(0.21)	
$\Delta Q * B_{100}$ (=1)	-	0.5569	0.5176
		(2.99)	(4.84)
$\Delta Q * B_{300}$ (=1)	-	-0.0078	-0.1736
		(0.04)	(2.25)
N	2,232	2,232	2,232

a. See text for a description of alternative model specifications and Appendix Table A.8 for the complete estimating equations and summary statistics.

When the output consistency dummy is introduced directly as a main effect, it accounts significantly for the score differential. It shows that the DEA (FREG) model systematically accords higher (lower) efficiency to hospitals with such divergent or segmented patterns of output, all else equal. Note that the net effects of size are significantly positive for smaller facilities, and significantly negative for larger facilities, net of the effect of output pattern. However, when the consistency dummy is interacted with size (the middle column), the main effects of each of the variables in question are indistinguishable from zero, though the interaction of inconsistent output and small bed size is now dramatically greater in magnitude and still significantly positive. In the right-most column, where the main effects of each variable have been omitted, each of the interaction terms is statistically significant and opposite in sign. It is of course unclear whether these differences imply "upward" biases in the DEA scores or, conversely, "downward" bias in the FREG values. What does seem clear, however, is that the estimates in Table 16 identify at least one major reason for the observed differential in the scores yielded by each model and, by implication, a set of factors that must be taken into account in interpreting levels and trends in inefficiency gauged by these two methods. We return to this point in the final section of this *Report*.

Reconciling the Results

In view of the confounding influences of size and control status on measured efficiency shown in the preceding section, we experimented with estimating several stratified DEA and FREG models. On the one hand, we partitioned the panel sample into three subgroups corresponding to the three bed size categories and estimated DEA and FREG models (identical to the main models reported above) for each subgroup. Difficulty was encountered in the FREG estimate of the largest bed size category, so we report the results only for the two smaller subgroups. On the other hand, we stratified the sample by control status, and estimated identical models for these sample subgrouping. We also encountered some difficulty here, which was overcome by combining the two proprietary categories and the voluntary and religious categories. Selected results from these efforts are presented in Table 18.

As can be seen, mean efficiency scores for these several sample subgroups differ, and in ways anticipated by the previous results. The DEA model attributes more efficiency to very small and medium size hospitals than does the FREG model; moreover, it finds greater variation across the ownership groupings, attributing in particular greater efficiency to proprietaries, and less to the religious and community controlled facilities. As a consequence, there is little change in the magnitude of the correlations between the DEA and FREG results from those observed previously, except perhaps for the case of the medium (101-299) bed size. The Pearson coefficient of 0.455 between the DEA and FREG scores for this latter strata is the highest of any DEA-FREG correlation reported in this study. Alas, most of the other correlation coefficients are only half again as great, suggesting that stratification per se is not likely to narrow the range of uncertainty about

Table 18
Selected Results, Stratified DEA and FREG Models[a]
By Size and Control, All Panel Hospitals, 1982-1993

Selected Results	Models Stratified By				
	Bed Size		Control		
	100 Beds or Less	101-299 Beds	Proprietary	Religious/ Voluntary	Govt
Efficiency Score					
DEA: Mean	0.894	0.904	0.918	0.825	0.873
Std.Dev.	0.126	0.111	0.102	0.141	0.031
FREG: Mean	0.824	0.825	0.848	0.853	0.914
Std.Dev.	0.100	0.108	0.086	0.082	0.134
Score Correlations					
Pearson: Coeff.	0.201	0.455	0.359	0.288	0.222
Prob.	0.0001	0.0001	0.0001	0.0001	0.0001
Spearman: Coeff.	0.204	0.376	0.338	0.327	0.298
Prob.	0.0001	0.0001	0.0001	0.0001	0.0001
N	479	1010	917	940	375

a. See text for a description of the stratified analyses.

the comparative performance of the DEA and FREG models in identifying efficient or inefficient hospitals and/or changes over time.

As an alternative means of reconciling the results of the two models, we carried out a Gedanken or "thought" experiment to see whether there would be greater concordance between the DEA and FREG results if we were able to neutralize or purge the effects of the size, output pattern and control status variations highlighted above. This experiment first used the version of the explanatory model with interaction terms for inconsistent output patterns to estimate DEA and FREG efficiency scores (i.e., the specification in Column 2, Appendix Table A.8 was used to reestimate the basic explanatory model that uses FREG and DEA scores as the dependent variable). Then the estimated parameters of this model were used to predict scores corrected for, or purged of, the effects of size and control. More particularly, we predict both DEA and FREG scores on the assumption that the size, output consistency, and religious/corporate proprietary net effects in each prediction model are identical. Since it is unclear whether DEA overstates, or FREG understates, these effects, we take the means of these disputed parameters of the two models, leaving all other model-specific coefficients the same.[13] These computations yield DEA and FREG scores corrected for the confounding influences of size, output pattern and control status. These values, labelled "purged" scores to distinguish them from others reported above, are then used to create overlapping partitions of efficient and inefficient hospitals akin to those used to initiate the analysis; see Table 14 above.

The results of this thought experiment are presented in Table 19. Three observations are warranted. The first is that using the purged scores does add to the number of hospitals identified simultaneously by both methods as either efficient or inefficient. This occurs because these corrected scores are now more highly correlated than their uncorrected counterparts in Table 13. Specifically, the Pearson coefficient for the purged scores is 0.732 ($p < 0.0001$) and the rank-order coefficient is 0.684 ($p < 0.0001$). As a result, about 80 additional

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[13] If $\beta_{i(DEA)}$ is one of the disputed coefficients from the DEA model and $\beta_{i(FREG)}$ is the corresponding coefficient from the FREG model, then the purged predictions use $\{(\beta_{i(DEA)} + \beta_{i(FREG)})/2\}$ for the net effect of the *ith* factor. Thus, the purged score for the *nth* observation (PS_n) in the DEA model is:

$$PS_{n(DEA)} = \Sigma_i\{(\beta_{i(DEA)} + \beta_{i(FREG)})/2\}X_{in} + \Sigma_k \beta_{k(DEA)} X_{kn}$$

while in the FREG model it is:

$$PS_{n(FREG)} = \Sigma_i\{(\beta_{i(DEA)} + \beta_{i(FREG)})/2\}X_{in} + \Sigma_k \beta_{k(FREG)} X_{kn}$$

where *i* indexes the size, output pattern and control status variables, and *k* indexes all other *RHS* variables in the model specification shown in Appendix Table A.8, Column 2.

Table 19
Selected Characteristics of Hospitals Classified
By Overlapping, Purged Efficiency Scores, Selected Time Periods, 1982-1993

Scoring Criteria/ Characteristics[a]	Mean Number or Proportion					
	1982-1993		1993		1982	
	Efficient	Inefficient	Efficient	Inefficient	Efficient	Inefficient
Top vs Bottom Quartiles						
Admissions	3422	12951	2176	14081	4377	14097
Length of Stay	5.7	7.1	5.4	6.3	6.3	7.5
Beds	113	451	95	510	119	437
Occupancy	48.1	60.0	36.4	52.9	62.9	72.2
FTEs per 100 Cases	7.8	9.5	10.3	11.4	6.5	8.1
Cost per Case	4107	5484	6821	8477	2088	3005
N	308	414	27	41	33	38
Above vs Below Median						
Admissions	4422	10532	3266	10157	6025	11022
Length of Stay	6.4	6.8	5.4	6.3	6.9	7.3
Beds	149	359	123	356	178	336
Occupancy	51.0	58.5	40.0	52.4	66.0	70.1
FTEs per 100 Cases	8.2	9.7	10.4	11.1	7.0	7.9
Cost per Case	4527	5600	6883	8491	2484	2848
N	820	1412	50	136	83	103

a. See text for a description of purged efficiency scoring and distribution cut points.

hospitals are now counted by both model in the *top* quartile and about twice as many are now judged inefficient. Furthermore, the characteristics of the hospitals now classified either in the top or bottom quartiles differ. Note, for example, the greater range of average bed sizes that are now included in the scoring range. Clearly, similar conclusions emerge for the classifications based on the more liberal criterion of above or below the overall median value.

Nonetheless, even with these corrected figures, the concordance of the two models is not measurably improved. They produce a conflicting picture of how much inefficiency remains in the industry and what facilities might be targeted in policy attempts to reduce it. Moreover, they provide little basis for judging whether, on average, efficiency relationships are improving over time. The Gedanken experiment, in other words, provides additional reason to suppose that the two models either tap significantly different dimensions of efficiency and/or that the influence of random or chance factors in the FREG formulation is sufficiently great to overshadow the degree to which each model is tapping efficiency.

CONCLUSIONS

A variety of substantive and methodological conclusions may be drawn from the preceding analyses. This final section catalogues the most important ones.

Substantively, we find a substantial and persistent amount of inefficiency in the way panel hospitals utilize resources. Despite slight variations by method and time point, we find overall inefficiency residuals (scores) on the general order of 14 (86) percent of the *best practice* level. This is quite consistent with the meager evidence that is already available in the literature (cf., Zuckerman et al., 1994). It is important to bear in mind that these inefficiencies are observed in hospitals in continuous operation over the period 1982-1993. Since we detect lower relative efficiency levels in surviving facilities that changed ownership or control during this period, we infer that non-survivors had low efficiency levels as well, perhaps even significantly lower ones. Unless these lower levels were offset by substantially more efficient facilities just opening their doors over the course of this time period, the overall level of inefficiency is probably higher than the 14 percent figure. Put somewhat differently, the average level of observed inefficiency that we find may actually understate the degree of inefficiency at the level of the level of the entire industry.

Either way, the level of measured inefficiency is sufficiently high to warrant the concern of policy makers. An obvious reason is that the costs of delivering hospital services are higher than they might otherwise be. For example, if all panel hospitals in 1993 had been *frontier-efficient*, total costs per case would have been lowered by roughly $1125 and, correspondingly, total cost-saving associated with all cases in that year would have added up to more than $1.7 billion. The entire industry is unlikely to be *frontier-efficient*, mostly because of chance occurrences that produce inefficiencies, if only for short periods of time. If the observed (mean) differential in the FREG and DEA efficiency scores is used as a rough indicator of the impact of these chance factors, then the most that might be expected is about 97 percent of the frontier level. Yet, even by this more charitable standard, frontier efficiency would have lowered per case costs to about $1095 and yielded a corresponding aggregate cost-savings of about $1.6 billion. Persistent inefficiency in the industry exacts a high economic toll.

Clearly, intensive hospital cost containment efforts, most notably those implemented over the period encompassed by this study, have not yet achieved measurable gains in efficiency. There are some reasons why the efficiency of Florida hospitals might not have been expected to improve much over the first half of the study period. For one thing, the high proportion of all Florida patients covered by Medicare and the comparatively high (blended) reimbursement rates during the phase-in of the Prospective Payment System probably moderated the pressure on hospitals to do more by way of changing input ratios and market specialization rates. For another, the state-level prospective budgetary review

process that was in place over this period used policy tools prior to 1989 that provided little stimulus to greater efficiency. However, these factors do not necessarily explain why inefficiency levels in the panel hospitals did not improve--and indeed might actually have worsened--over the second half of the study period. Our findings in this regard strongly suggest that PPS reimbursement levels and prospective budgets approved by the state were insufficient inducements to greater efficiency. Of course, the conclusion that PPS and/or state budgetary review failed in any way to change efficiency relationships may not be warranted, in part because inefficiency might actually have been even higher had these policies never been initiated, and in part because efficiency gains may require a long lag time. Our point is simply that these policy interventions did not produce measurable net gains in efficiency relationships over the period encompassed by the data analysis.

Some reasons why public policy efforts have yet to produce efficiency gains are suggested by several other substantive results of the statistical analysis. The significant influences of internal and external competitive pressures on efficiency levels are particularly important in this regard. A consistent finding in the analysis of efficiency correlates is that net investments and the size/composition of the hospital's medical staff are inversely related to efficiency scores. The FREG results also consistently find that competitive pressures in the local health care market are inversely related to efficiency. This set of interrelated results would be expected if policy efforts failed to curb unwarranted growth and diffusion of medical technology; it would also be expected if hospitals continued to engage in non-price competition for physicians and patients. It is worth recalling here that the analysis uses an index of local competitive pressure that accounts for, among others, historical changes in HMO penetration, alternative delivery mechanisms and physician supply. The continuing reliance on non-price strategies in response to local competitive pressures must surely be a key to understanding the absence of efficiency gains in panel hospitals (cf., Chirikos, 1992). Whether very recent changes in local competitive dynamics, particularly the spectacular growth of managed care networks in Florida since 1992, at long last alters this behavior will thus be a decisive factor shaping future trends in efficiency levels.

Another result worth highlighting is the mixed and ambiguous impact of hospital ownership on efficiency levels. On the one hand, the analysis pointed consistently to higher efficiency levels in hospitals under government control than in voluntary hospitals. This difference, which has also been detected in some other studies, may reflect indirectly the influence that amenity level has on the costs of care (cf., Ozcan, et al., 1992). The high proportion of ownership changes in the panel sample of hospitals involving private sector acquisitions of public facilities may also help explain the downturn in average (panel) efficiency scores over the study period. More interesting perhaps are the mixed findings relating to the relative efficiency of proprietary versus voluntary hospitals. These ambiguous results

should not arise if investor-owned managements indeed operate more efficiently. The high proportion of Florida hospitals that are investor-owned has thus not contributed to the efficiency of the hospital industry in the State.

These substantive conclusions suggest the need for more attention to reimbursement strategies at all levels. For instance, even with frequent rebasing, the findings imply that the "standard" PPS rate and the related vector of DRG "weights" embody a significant amount of inefficiency. Furthermore, because the results clearly show that hospitals differ both by efficiency level and the corresponding institutional capacity to deal with it, blending the cost/efficiency conditions of the hospital into the reimbursement formula may be necessary (cf., Coulam and Gaumer, 1991; Pope, 1990). Whether analyses of the sort carried out here can actually quantify how much inefficiency exists is thus crucially important to efforts to design more effective reimbursement formulae.

Two methodological findings of the present study are highly significant in regard to the design of such reimbursement policy:

1. The specific method used to measure inefficiency portrays the attributes or characteristics of the most "efficient" hospital in significantly different terms. In contrast to the FREG counterpart, the DEA method is found generally to score efficiency higher in facilities of smaller size and lower in larger size ones. Relative to FREG, the DEA model also scores religious-affiliated hospitals lower and, at times, proprietary hospitals higher, than voluntary hospitals. For its part, the FREG model tends to accord higher efficiency scores to hospitals paying wages above the local market average and, in many cases, lower scores to facilities located in more competitive local health care markets. In our judgment, the fact that the FREG estimates tend more often to implicate economic factors in observed inefficiency is not simply coincidence. We infer from this that the two methods are tapping somewhat different dimensions (or different types of) efficiency. We also infer that the differences in the efficiency scoring of the two methods are not simply attributable to the chance factors that are encompassed by the FREG model and omitted in the DEA model.

2. Given the method, model specification itself does not appear to matter as much as initially supposed. Although only a limited number of sensitivity tests of different model specifications were carried out, they nonetheless suggested that the efficiency results (i.e., the scores yielded by each method) do not change dramatically when specifications are altered. Whether this would continue to hold if the number of inputs and outputs were disaggregated into ever larger numbers of more homogenous categories is unclear. Greater disaggregation inevitably compounds problems in running the FREG model, because it is already burdened with a large number of regressors. It might also compound the logistics of running the DEA model as well. It is worth repeating in this context that DEA estimation is very time-consuming. The FREG

method affords greater flexibility in specification search than does the DEA approach because it takes less time to implement.

The findings of this study are sufficiently encouraging to warrant more intensive research efforts in the future. Three priorities stand out. One is to replicate comparative analyses of DEA and FREG along the lines pursued here with other data sets. Although we believe the Florida data are generalizable to the national hospital market, this proposition ultimately must be tested more directly. Replication studies may not be easy to conduct, in part because national panel data sets are not as detailed as the set used here. Nonetheless, if such studies can be conducted, and if they confirm that DEA and FREG approaches do yield different results, then the substantive issues and methodological puzzles uncovered in the present study must be accorded serious consideration.

Another issue that future studies must investigate more systematically is how best to partition the sample at hand. In the case of panel data, the question relates to the length of time a particular regime of technological constraints and choices should be modeled. When national data are used, the impacts of differences in regulatory and other policy environments must also be modeled. Because the annual cross-sections varied substantially, we relied heavily in this study on the pooled cross-section across the entire 12-year period. Although we conducted sensitivity tests, the possibility still exists that some aspects of our finding are artifacts of this partitioning schema and the way in which we used it.

Finally, the long-standing issue of how best to measure hospital output must be tackled in more clever ways in future studies. One question is the degree to which output indexes pick up the impact of changes in patient populations and the severity of the health problems that bring those populations to the hospital. We believe that the use of a case mix-weighted admission index captured these effects, but surely there are other measures that might perform even better. More significant, however, is the finding in this study that the "consistency" of output patterns (as we called them above) plays a key role in creating divergent results of the DEA and FREG models. These patterns, coupled to control status and size, accounted for a large part of the discrepancy between the DEA and FREG efficiency scores. Additional work along these lines may suggest methods for aggregating or classifying hospital output that would serve to bring DEA and FREG scoring closer together. In the absence of such additional research, the identification of "efficient" hospitals for purposes of reimbursement and cost containment policies will remain difficult to achieve and heavily dependent on the choice of method.

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Appendix Table A.1
Variable Definitions and Data Sources[a]

Variables	Definitions/Sources
Admissions	Reported number of admissions to acute and intensive care service centers for all payor groups, including Medicare, Medicaid and commercial HMOs; insurance charge-based; and self-pay in year t (t = 1, 2, . . . , 12). (Source: Reports).
ADS Development	Vector of dummy variables characterizing the extent to which alternative delivery system or substitute hospital services developed over the study period in the county in which the hospital is located, as indicated primarily by the number of free-standing ambulatory surgery centers in operation at various points in time. Substantial development is indicated by at least two such centers in the period prior to 1986, three or more in the period 1986-1987, four or more in 1988, seven or more between 1989-1991, and ten or more after 1991. Minimal development refers to no more than one such center in any given year of the study period. Moderate development, the omitted group, includes any development pattern not encompassed by the other two mutually-exclusive categories. (Source: Authors' estimates based on Atlas and other unpublished materials).
Beds	Unless otherwise noted, the number of acute, intensive, and subacute beds reported by the hospital in year t as available beds. (Source: Reports).
Capital Assets	
Plant and Related	Reported dollar value of beginning balance of assets in land, land improvements, buildings, leasehold improvements, and construction in progress in year t. (Source: Reports).
Equipment	Reported dollar value of beginning balance of assets in fixed and movable equipment in year t. (Source: Reports).
Total Current	Reported dollar value of total current assets in 1) cash, accounts receivable, and inventories, and 2) assets whose use is limited, intangible and tangible alike in year t. (Source: Reports).
Capital Expenses	
Plant and Related	Net difference between reported accumulated depreciation at the beginning of year t and the end of that year, including accumulated depreciation adjustments for land, building, and leasehold improvements. (Source: Reports).
Equipment	Net difference between reported accumulated depreciation charges at the beginning of year t and the end of that year, including accumulated depreciation adjustments for fixed and movable equipment. (Source: Reports).
Interest	Reported expenses for both long-term and short-term interest payments. (Source: Reports).

Appendix Table A.1 (Continued)
Variable Definitions and Data Sources[a]

Variables	Definitions/Sources
Total Capital Expense	Total of plant depreciation, equipment depreciation, and interest charges in year t.
Case Mix	Mean DRG weight for hospital in year t. Values for 1982-83 were extrapolated from available series by the authors. (Source: ACHA/HCCB).
Case Mix-Weighted Admission	Index created by multiplying admissions to case mix index in year t.
Control Status	Vector of dummy variables characterizing the control or ownership status of the hospital in year t. Four mutually-exclusive control categories take the value of one: proprietary corporations indicate investor-owned facilities not owned by single individuals or partnerships; other proprietaries indicate all other investor-owned facilities; religious-affiliated institutions are non-profit hospitals owned by various church-related groups; and government hospitals are public sector hospitals at all levels of local and state government. The fifth category, which is the omittedgroup in this dummy vector, refers to non-profit voluntary or community hospitals. (Source: Reports).
Elderly Population	Percent of the total population that is 65 years of age or older in the county in which the hospital is located. (Source: Abstract).
FTE Personnel	Reported number of Full-Time Equivalent employees on the hospital's payroll by cost center in year t (calculated to the nearest tenth). Patient care cost centers include hospital services (e.g., medical/surgical acute, obstetrics, neonatal ICU, coronary care, etc.), ambulatory (e.g., clinic services, emergency services, free-standing clinics, home health, etc.), and ancillary services (e.g., labor and delivery services, anesthesiology, laboratory services, radiology, c-t scan, physical therapy, etc.). Administrative cost centers include all other hospital services such as dietary and cafeteria, laundry, plant operation, pharmacy, accounting, etc. (Source: Reports).
HMO Penetration	Vector of dummy variables characterizing the extent of HMO development over the study period in the county in which the hospital is located. Substantial development is indicated by penetration rates exceeding 3.5 percent in the period prior to 1987 and more than five HMOs in operation after 1987. Minimal development refers to the absence of any HMO prior to 1987 and no more than one such plan after that year. Moderate development, the omitted group, includes any development pattern not encompassed by either of the two other mutually-exclusive categories. (Source: authors' estimates based on Atlas and other unpublished materials).
Hospital Competitors	Dummy vector characterizing the number of competitors in the hospital's primary market. The omitted category is zero competitors, i.e., a monopoly market (Source: authors' estimates based on discharge records)
Local Health Care Market	One of 59 areas delineated by analyzing 1987 discharge records of patient-origin by zip code. See text for description.

Appendix Table A.1 (Continued)
Variable Definitions and Data Sources[a]

Variables	Definitions/Sources
Local Wage Rates	Dummy vector characterizing the extent to which the hospital's wage rates exceed or fall short of the local market average. Above local average takes the value of one if the hospital's wage payments for hospital services, ancillary, and administrative personnel were each above their respective local averages, zero otherwise. Below average payments refer to the same three categories. The omitted group, in effect, is comprised of hospitals paying mean wages or operating in monopoly markets. (Source: Reports).
Market Share	Hospitals are primary competitors in market areas (defined above) in which they deliver the largest portion of their output. Secondary competitors are typically larger referral centers serving a broader region comprised of several local markets that compete with institutions in each locality. Market shares, in turn, are computed for an individual hospital in year $\underline{t}$ as the weighted average of the hospital's percentage of total output in the local market (admissions) in the three largest markets in which it competes, using the fractions of total output delivered to each local market as weights. (Source: Authors' estimates based on discharge records and Reports).
Net Annual Investment	The difference in year $\underline{t}$ between the beginning balance of all capital assets and the ending balance of these assets, net of reported capital disposals and transfers. (Source: Reports).
Nursing Home Bed Supply	Number of nursing home beds in the county in which the hospital is located. (Source: <u>Atlas</u>).
Operating Expenses	Reported dollar expenses by type and cost center in year $\underline{t}$. Salaries and wages include direct expenditures on personnel on the hospital's payroll net of fringe benefit payments, i.e., FICA, pension, etc. Other expenses include all other operating expenses, inclusive of fringe benefits to personnel. See FTE Personnel above for delineation of cost centers. (Source: Reports).
Outpatient Indexes	
Case-equivalents	Index constructed as $(A_t(1 + \underline{rr}_i)) - A_t$ where A_t represents admissions to the hospital in year $\underline{t}$ and $\underline{rr}_i$ represents the ratio of outpatient revenue generated in ancillary and hospital service centers to total revenue generated in all inpatient, patient care centers in year $\underline{t}$. (Source: Reports).
ER-equivalents	Index constructed as $ER_t(1 + \underline{rr}_j)$ where ER represents reported emergency room visits and $\underline{rr}_j$ represents the revenue ratio between all ambulatory activity other than emergency services (including total renal dialysis services) and revenue generated in emergency services in year $\underline{t}$. (Source: Reports).

Appendix Table A.1 (Continued)
Variable Definitions and Data Sources[a]

Variables	Definitions/Sources
Outpatient Activities	
Emergency Services	Reported number of emergency service visits including 24 hour/inhouse MD and 24 hour/MD on call in year t. (Source: Reports).
Ambulance Services	Reported number of ambulance trips in year t. (Source: Reports).
Ambulatory Surgeries	Reported number of total ambulatory surgery "minutes' in year t. (Source: Reports).
Dialysis Treatments	Reported number of inpatient and outpatient renal dialysis treatments in year t. (Source: Reports).
Ownership Change	Dummy variable taking the value of one if the hospital reported either a a change in ownership and/or a change in control status in year t, zero otherwise. (Source: Reports).
Patient Days	Reported number of patients days in medical and surgical (med/surg) acute, other acute, and intensive service centers in year t. (Source: Reports).
Patient Care Revenue Ratio	The proportion of a hospitals total revenues in year t accounted for by revenues from all patient care centers. (Source: Reports).
Physician Staff Mix	Index constructed in reference to the number of clinical specialties represented on the hospital's medical staff as reported by the hospital in year t. (Source: Reports).
Physician Supply	Number of physicians (MDs and DOs) per 100,000 population in the county in which the hospital is located. (Source: Abstract).
Population Density	Total population per square mile in the county in which the hospital is located. (Source: Abstract).
Service Mix	Dummy vector based on the hospital's service index score relative to the average score in the primary market in which it is a competitor. The index itself is a resource-weighted inventory of the number of specialized services offered by the hospital in a given year, e.g., neurological surgery, open heart surgery, burn intensive care, occupational therapy cardiac catheterization laboratory, etc. (Source: ACHA/HCCB.) The index score in year t is compared to the mean of the primary market as defined above. One dummy variable takes the value of one if the value is above the local market average, zero otherwise. Another takes a value of one if it is below that average, zero otherwise. This implies that the omitted category is comprised of average hospitals and those operating in a monopoly primary market.

a. Unless otherwise noted, the primary data sources are as follows: information derived from the annual ACHA/HCCB financial reports (denoted simply as Reports); data taken from various issues of Shyeyen (ed.) Florida Statistical Abstract (denoted simply as Abstract); and information derived from the State of Florida, Health Care Atlas (denoted simply as Atlas).

Appendix Table A.2
Frontier Regression Estimates of Total Cost Function, Trans-Log Specification A, Panel and Selected Annual Cross-Sections, 1982-1993

Model Parameters[a]	Maximum Likelihood Coefficients (Absolute t-ratios)						
	Panel	Selected Annual Cross-Sections					
	1982-1993	1993	1991	1989	1987	1986	1983
β_1	0.2712	0.8515	-0.8792	-0.5972	-0.3170	0.2268	-0.0943
	(3.24)	(1.43)	(1.69)	(1.35)	(0.55)	(0.53)	(0.14)
β_2	-0.0218	0.3608	-0.4287	-0.2120	-0.2038	-0.0060	-0.0032
	(0.95)	(0.20)	(2.18)	(1.29)	(1.76)	(0.06)	(0.03)
β_3	0.7650	0.2757	-0.1545	0.0086	0.0147	-0.4088	0.0923
	(10.95)	(0.63)	(0.38)	(0.02)	(0.03)	(1.03)	(0.16)
β_4	-1.30	-0.5550	2.4075	1.5105	0.0026	-0.1675	-0.2588
	(8.47)	(0.53)	(2.26)	(1.70)	(0.00)	(0.18)	(0.18)
β_5	0.6782	-0.1762	-0.3115	0.3601	0.7299	1.3104	0.4550
	(11.87)	(0.31)	(0.55)	(0.76)	(1.60)	(3.03)	(0.94)
β_6	0.9800	0.1313	0.2905	-0.0556	0.2271	0.0333	0.1300
	(3.16)	(0.63)	(1.07)	(0.19)	(1.09)	(0.16)	(0.16)
γ_1	-0.8379	6.0961	-3.0239	2.1825	3.0897	10.3110	12.878
	(3.44)	(0.74)	(0.42)	(0.43)	(0.95)	(0.86)	(1.70)
γ_2	2.4569	-23.5820	-2.2169	9.6450	3.9171	-12.73	4.8547
	(4.29)	(1.34)	(0.36)	(1.59)	(1.67)	(2.02)	(0.82)
γ_3	-2.8104	10.375	-7.5731	-19.5730	-8.6353	-3.3481	-2.2918
	(2.45)	(1.64)	(1.21)	(2.91)	(1.80)	(0.21)	(0.30)
γ_4	-0.0742	-0.0332	-0.0505	0.0131	0.0384	-0.0522	0.0363
	(10.65)	(0.88)	(1.24)	(0.25)	(0.62)	(0.92)	(0.90)
5	0.0377	0.0644	-0.0184	0.0415	-0.0300	0.0490	0.6856
	(4.48)	(1.51)	(0.48)	(0.87)	(0.57)	(0.90)	(0.19)
6	0.0573	0.0848	0.0423	0.0503	0.1117	0.0349	0.0209
	(8.52)	(2.09)	(0.85)	(1.14)	(2.32)	(1.07)	(1.05)
β_{11}	0.0299	0.1254	0.1416	-0.0017	0.2610	0.1007	0.0117
	(4.96)	(1.63)	(1.16)	(0.03)	(1.62)	(1.10)	(0.08)
β_{22}	0.0020	-0.0090	-0.0072	0.0034	0.0005	-0.0022	0.0013
	(2.67)	(0.86)	(0.63)	(0.76)	(0.19)	(0.91)	(0.54)
β_{33}	0.0333	-0.0633	0.1362	0.0052	0.1080	-0.0257	0.0282
	(2.14)	(0.77)	(1.54)	(0.08)	(0.88)	(0.28)	(0.15)
β_{44}	0.3752	0.2414	0.4920	0.0940	0.6752	0.0344	-0.8326
	(0.66)	(0.77)	(1.31)	(0.31)	(1.05)	(0.08)	(1.21)
β_{55}	0.0270	0.1039	0.1653	0.1273	0.0427	0.0819	-0.0260
	(2.86)	(1.73)	(2.13)	(2.04)	(0.64)	(0.85)	(0.34)
β_{66}	0.0100	-0.0054	0.0185	0.0036	0.0149	0.0098	0.0020
	(11.32)	(0.34)	(4.03)	(0.09)	(2.34)	(0.98)	(0.30)
γ_{11}	0.6660	-0.3005	0.1694	-0.1020	-0.1448	-0.5049	-0.6357
	(5.30)	(0.72)	(0.47)	(0.39)	(0.87)	(0.83)	(1.64)
γ_{22}	-0.1384	1.1795	0.1115	-0.5045	-0.2266	0.6390	-0.2663
	(4.65)	(1.32)	(0.36)	(1.63)	(1.82)	(1.99)	(0.87)
γ_{33}	0.1652	-0.5228	0.3886	1.0304	0.4776	0.1837	0.1437
	(2.64)	(1.60)	(1.19)	(2.93)	(1.86)	(0.22)	(0.36)
γ_{44}	-0.0039	-0.0014	-0.0031	0.0004	0.0043	-0.0030	0.0020
	(10.02)	(0.63)	(1.42)	(0.11)	(0.92)	(0.65)	(0.89)
γ_{55}	0.0025	0.0042	-0.0007	0.0025	-0.0068	0.0043	0.0002
	(4.69)	(0.45)	(0.35)	(0.65)	(1.15)	(0.84)	(0.11)
γ_{66}	0.0032	0.0079	0.0043	0.0036	0.0093	-0.0008	0.0009
	(5.11)	(1.84)	(0.68)	(0.77)	(1.58)	(0.02)	(0.41)

Appendix Table A.2 (Continued)

Model Parameters[a]	Maximum Likelihood Coefficients (Absolute t-ratios)						
	Panel	Selected Annual Cross-Sections					
	1982-1993	1993	1991	1989	1987	1986	1983
β_{12}	-0.0356	-0.0029	-0.0725	-0.0604	-0.0173	-0.0597	-0.0300
	(6.47)	(0.04)	(1.44)	(1.33)	(0.47)	(2.04)	(1.13)
β_{13}	-0.1068	0.1046	0.0951	-0.1449	0.0824	-0.1848	-0.5272
	(4.16)	(0.82)	(0.58)	(1.02)	(0.40)	(1.03)	(1.98)
β_{14}	0.0968	-0.3264	-0.4350	0.0385	-0.6831	-0.0560	0.7216
	(2.34)	(1.03)	(1.05)	(0.14)	(1.15)	(0.14)	(1.22)
β_{15}	-0.0689	-0.0631	0.2031	0.1513	0.0704	-0.0253	-0.0783
	(3.34)	(0.42)	(1.40)	(1.24)	(0.45)	(0.17)	(0.50)
β_{16}	0.0177	-0.0711	0.0267	0.1086	0.0291	0.0907	-0.0375
	(1.43)	(1.17)	(0.38)	(1.18)	(0.33)	(1.10)	(0.30)
β_{23}	0.0149	0.0539	-0.0609	-0.0549	-0.0129	-0.0369	0.0096
	(2.56)	(1.07)	(1.35)	(1.50)	(0.39)	(1.18)	(0.33)
β_{24}	0.2448	0.0626	0.1687	0.1301	0.2772	0.0728	0.0177
	(2.17)	(0.62)	(2.49)	(2.17)	(0.47)	(1.19)	(0.40)
β_{25}	-0.0041	-0.1113	0.0048	0.0167	0.4368	0.0139	-0.0099
	(0.90)	(2.85)	(0.12)	(0.46)	(0.15)	(0.58)	(0.48)
β_{26}	0.0036	-0.0077	0.0260	0.0003	0.2169	0.0246	0.0125
	(1.41)	(0.33)	(1.15)	(0.02)	(1.85)	(1.82)	(1.45)
β_{34}	0.0195	-0.0055	-0.2530	0.2177	-0.2432	0.3771	0.6779
	(0.34)	(0.02)	(0.79)	(0.72)	(0.47)	(0.95)	(1.03)
β_{35}	-0.0621	0.3298	-0.0274	-0.1192	0.0075	-0.0321	-0.1499
	(3.35)	(0.29)	(0.24)	(0.99)	(0.05)	(0.23)	(1.07)
β_{36}	-0.0059	-0.0532	-0.0121	0.0845	-0.5054	0.0182	-0.0129
	(0.59)	(1.00)	(0.23)	(1.04)	(0.68)	(0.27)	(0.19)
β_{45}	0.0385	-0.1399	-0.5005	-0.4167	-0.2726	-0.2657	0.1947
	(0.91)	(0.58)	(2.15)	(2.17)	(0.83)	(0.92)	(0.61)
β_{46}	-0.0491	0.0547	-0.1574	-0.2923	-0.0739	-0.1918	0.0012
	(2.22)	(0.57)	(1.38)	(2.02)	(0.50)	(1.34)	(0.01)
β_{56}	0.0086	0.1077	0.0578	0.1031	0.0334	0.0426	0.0469
	(1.55)	(2.37)	(1.07)	(1.66)	(0.71)	(0.75)	(0.77)
α_0	14.1000	45.2380	69.20	44.0160	16.92	35.43	-66.9[illegible]
	(2.46)	(0.68)	(1.92)	(2.87)	(0.62)	(0.40)	(1.21)
$\sigma u/\sigma v$	1.5279	17.61	2.6219	1.9734	6.7509	0.8734	0.6829
	(18.67)	(0.48)	(3.35)	(3.65)	(1.31)	(1.40)	(0.60)
$\sqrt{\sigma^2 v+\sigma^2 u}$	0.2152	0.1906	0.1620	0.1743	0.2120	0.1363	0.1424
	(35.40)	(14.81)	(9.46)	(6.90)	(11.55)	(3.85)	(2.16)
N	2,232	186	186	186	186	186	186
Ln Cost: Mean	16.853	17.078	17.038	16.902	16.801	16.787	16.691
Std.Dev.	1.020	1.056	1.011	1.028	1.029	0.998	0.988
Log-likelihood	917.78	163.38	156.50	129.70	136.71	136.91	119.74

a. See text equation (6a) for parameter notation and the text for a discussion of model specification.

Appendix Table A.3
Frontier Regression Estimates of Total Cost Function, Trans-Log Specification B,
Panel and Selected Annual Cross-Sections, 1982-1993

Model Parameters[a]	Maximum Likelihood Coefficients (Absolute t-ratios)						
	Panel	Selected Annual Cross-Sections					
	1982-93	1993	1991	1989	1987	1985	1982
β_1	0.2293	0.1521	-0.2664	0.1823	-0.0753	-0.0309	0.4028
	(4.75)	(0.40)	(0.96)	(0.44)	(0.19)	(0.05)	(1.04)
β_2	0.0061	-0.0201	-0.0012	-0.0385	0.0099	0.0161	0.0232
	(0.91)	(0.16)	(0.02)	(0.65)	(0.53)	(0.74)	(1.35)
β_3	0.5539	0.4778	0.3976	0.6073	0.1623	-0.0196	-0.0442
	(7.70)	(1.72)	(1.10)	(1.63)	(0.36)	(0.04)	(0.10)
β_4	-1.1509	-0.6756	-0.4027	-1.2530	-1.2140	-0.3099	-0.2919
	(9.38)	(1.08)	(0.76)	(1.77)	(1.32)	(0.25)	(0.34)
β_5	0.7237	0.1652	0.4297	0.4145	0.8581	1.1822	0.4416
	(10.48)	(0.40)	(0.98)	(1.11)	(2.32)	(2.74)	(1.09)
β_6	0.1383	0.5106	0.7403	0.3998	0.0853	0.0573	0.4029
	(4.44)	(2.86)	(3.54)	(1.56)	(0.47)	(0.25)	(2.38)
γ_{1*}	0.5376	0.3519	0.4807	0.2233	0.5572	0.2173	0.4188
	(36.88)	(3.11)	(4.40)	(1.99)	(6.51)	(3.77)	(8.62)
γ_{2*}	-0.0459	0.0653	0.1200	-0.8480	-0.1329	-0.0463	-0.0688
	(2.41)	(0.57)	(1.00)	(0.01)	(1.39)	(0.37)	(0.70)
γ_{3*}	0.4790	0.5484	0.3670	-0.7470	0.5418	0.8161	0.6023
	(22.59)	(5.75)	(2.81)	(5.22)	(5.35)	(6.30)	(6.17)
γ_{4*}	-0.0050	-0.0051	0.0112	-0.0089	-0.0169	-0.0355	0.0077
	(2.53)	(0.67)	(1.03)	(0.70)	(1.13)	(2.73)	(1.01)
γ_{5*}	0.0055	0.0137	0.0018	0.0092	0.0210	0.1029	0.0203
	(1.80)	(1.42)	(0.20)	(0.50)	(1.08)	(0.48)	(1.47)
β_{11}	-0.0227	-0.0130	0.0061	-0.0134	0.0026	-0.0129	-0.0402
	(6.57)	(0.55)	(0.35)	(0.52)	(0.12)	(0.36)	(1.77)
β_{22}	-0.0013	0.0012	-0.007	0.0018	-0.0011	-0.0033	-0.0037
	(1.66)	(0.12)	(0.13)	(0.32)	(0.46)	(1.28)	(1.70)
β_{33}	-0.0356	-0.0221	-0.0172	-0.0262	-0.0066	-0.0016	-0.0082
	(8.05)	(1.30)	(0.82)	(1.05)	(0.25)	(0.05)	(0.30)
β_{44}	0.2483	0.0247	0.0877	-0.3559	-0.1865	0.0486	-0.0112
	(5.32)	(0.11)	(0.37)	(0.87)	(0.45)	(0.13)	(0.03)
β_{55}	0.0309	0.0952	0.0537	0.0094	0.0782	0.0478	0.0337
	(5.34)	(2.07)	(0.80)	(0.16)	(1.66)	(0.78)	(1.04)
β_{66}	0.0110	0.0032	0.0158	0.0119	0.0092	0.0087	0.0126
	(13.88)	(0.27)	(4.64)	(1.70)	(1.64)	(2.05)	(2.25)
β_{77}	0.1916	0.0611	0.1384	-0.2698	-0.1033	0.1133	0.0883
	(5.69)	(0.35)	(0.82)	(0.94)	(0.33)	(0.39)	(0.32)
β_{47}	-0.2701	0.0719	-0.0688	0.7775	0.4666	-0.0174	0.0591
	(3.29)	(0.17)	(0.16)	(1.13)	(0.63)	(0.03)	(0.09)
β_{57}	-0.0942	-0.0141	-0.1094	-0.0483	-0.1799	-0.1725	-0.0762
	(10.19)	(3.01)	(1.27)	(0.58)	(2.41)	(1.91)	(1.35)
β_{67}	-0.0027	-0.0507	-0.0954	-0.0587	-0.0209	-0.0187	-0.0572
	(7.24)	(1.77)	(3.69)	(1.88)	(0.85)	(0.65)	(2.93)
α_0	0.8342	0.0345	-1.2869	1.497	4.46	-0.2132	-1.4801
	(3.76)	(0.03)	(1.13)	(1.31)	(5.13)	(0.16)	(1.04)
$\sigma u/\sigma v$	1.7103	2.9599	3.5880	3.357	2.6855	0.9844	1.0937
	(22.23)	(4.10)	(3.99)	(4.85)	(4.33)	(2.84)	(2.27)
$\sqrt{\sigma^2 v+\sigma^2 u}$	0.2366	0.2164	0.2433	0.2979	0.2280	0.1743	0.1760
	(49.23)	(13.17)	(17.23)	(15.63)	(11.02)	(6.87)	(4.23)

Appendix Table A.3 (Continued)

Model Parameters[a]	Maximum Likelihood Coefficients (Absolute t-ratios)						
	Panel	Selected Annual Cross-Sections					
	1982-1993	1993	1991	1989	1987	1985	1982
N	2,232	186	186	186	186	186	186
Log-likelihood	796.91	107.34	92.54	53.00	93.44	96.31	99.21

a. See text equation (6b) for parameter notation and the text for a discussion of model specification.

Appendix Table A.4
Regression Estimates, Determinants of Local Market Share,[a]
All Panel Hospitals, 1982-1993

Explanatory Variables[b]	Means (Std. Dev.)	OLS Coefficients (Absolute t-ratios)
Number of Hospital Competitors		
One-Four	0.409	-0.4100
	(0.492)	(32.83)
Five and More	0.484	-0.5772
	(0.499)	(40.53)
Physician Supply	223.34	0.0879E-03
	(104.54)	(1.96)
HMO Penetration		
Minimal	0.238	-0.0310
	(0.426)	(2.99)
Substantial	0.193	-0.0023
	(0.395)	(0.15)
ADS Development		
Minimal	0.275	0.0227
	(0.446)	(2.19)
Substantial	0.336	-0.0125
	(0.472)	(1.38)
Nursing Home Bed Supply	2624.1	-0.0044E-03
	(2475.8)	(1.25)
Real Income	15091.0	-0.0017E-03
	(4858.9)	(1.76)
Population Density	641.25	0.0029E-03
	(719.25)	(0.33)
Percent Population Elderly	0.185	0.3257
	(0.069)	(5.48)
Constant	-	0.6435
		(35.08)
N	2,232	2,232
Dependent Variable: Mean	-	0.236
Standard Deviation	-	0.240
R-squared (adj.)		0.558

a. See text for a description of the market share variable.

b. See Appendix Table A.1 for variable definitions and data sources.

Appendix Table A.5
Regression Estimates, Random Effects Models of FREG and DEA Efficiency Scores,
Final Cross-Sectional Specification,[a] All Hospitals, 1982-1993

Explanatory Variables[b]	Means (Std. Dev.)	GLE Coefficients (Absolute t-ratios) FREG Scores	DEA Scores
Control: Religious (=1)	0.074	0.0012	-0.0332
	(0.262)	(0.08)	(3.42)
Proprietary Corporation (=1)	0.376	0.0162	0.0090
	(0.485)	(2.00)	(1.57)
Other Proprietary (=1)	0.034	0.0073	0.0148
	(0.183)	(0.52)	(1.41)
Government (=1)	0.168	0.0325	0.0115
	(0.374)	(3.59)	(1.73)
Ownership Change (=1)	0.051	-0.0232	0.0059
	(0.220)	(2.72)	(0.89)
Beds: 100 or Fewer (=1)	0.218	-0.0227	0.0031
	(0.413)	(2.44)	(0.46)
300 or More (=1)	0.324	0.0162	0.0084
	(0.468)	(1.92)	(1.40)
Physician Staff Mix (Index/100)	0.194	-0.1098	-0.0219
	(0.072)	(2.21)	(0.58)
Wage Rates: Above Local Average (=1)	0.224	0.0292	-0.0018
	(0.417)	(5.68)	(0.44)
Below Local Average (=1)	0.234	-0.0405	0.0107
	(0.423)	(7.91)	(2.71)
Net Annual Investment ($ Millions)	3.965	-0.0006	0.0004
	(8.094)	(2.26)	(1.89)
Service Mix: Above Local Average (=1)	0.141	0.0043	0.007[illegible]
	(0.348)	(0.50)	(1.19)
Below Local Average (=1)	0.108	0.0002	0.0054
	(0.310)	(0.02)	(0.86)
Patient Care Revenue Ratio	0.968	0.1091	0.1944
	(0.048)	(1.69)	(4.03)
Market Share (Endogenous Percent)	0.236	0.0419	0.0142
	(0.178)	(1.74)	(0.88)
Constant	-	0.7612	0.7685
		(11.98)	(16.25)
N	2,232	2,232	2,232
Efficiency Score: Mean	-	0.862	0.968
Standard Deviation	-	0.10	0.07
Lagrange Multiplier Test	-	748.05	359.88
Hausman Test	-	0.000	0.000
R-squared	-	0.085	0.037

a. See text for a description of alternative model specifications.

b. See Appendix Table A.1 for variable definitions and data sources.

Appendix Table A.6
Regression Estimates, Random Effects Models of FREG and DEA Efficiency Scores, Alternative Specifications,[a] All Hospitals, 1982-1993

Explanatory Variables	Means (Std. Dev.)	GLE Coefficients (Absolute t-ratios) FREG Model A	Unadjusted DEA
Control: Religious (=1)	0.074	0.0320	-0.0222
	(0.262)	(2.66)	(0.94)
Proprietary Corporation (=1)	0.376	0.0066	0.0167
	(0.485)	(1.02)	(1.22)
Other Proprietary (=1)	0.034	0.0230	-0.0395
	(0.183)	(2.28)	(1.62)
Government (=1)	0.168	0.0381	0.0213
	(0.374)	(5.67)	(1.36)
Ownership Change (=1)	0.051	-0.0081	0.0294
	(0.220)	(1.40)	(1.95)
Beds: 100 or Fewer (=1)	0.218	-0.0110	0.0151
	(0.413)	(1.53)	(0.94)
300 or More (=1)	0.324	0.0139	-0.0139
	(0.468)	(2.10)	(0.97)
Physician Staff Mix (Index)	0.194	-0.0011	-0.0084
	(0.072)	(0.31)	(9.69)
Wage Rates: Above Local Average (=1)	0.224	0.0151	-0.0185
	(0.417)	(4.33)	(2.04)
Below Local Average (=1)	0.234	-0.0097	-0.0016
	(0.423)	(2.77)	(0.18)
Net Annual Investment ($ Millions)	3.965	-0.0007	-0.0040
	(8.094)	(3.87)	(8.50)
Service Mix: Above Local Average (=1)	0.141	0.0055	0.0183
	(0.348)	(0.89)	(1.24)
Below Local Average (=1)	0.108	0.0032	0.0007
	(0.310)	(0.53)	(0.05)
Patient Care Revenue Ratio	0.968	0.2070	-0.0537
	(0.048)	(4.45)	(0.48)
Market Share (Endogenous Percent)	0.236	0.0957	0.0555
	(0.178)	(4.24)	(1.39)
Constant	-	0.6230	0.9238
		(13.55)	(8.38)
N	2,232	2,232	2,232
Efficiency Score: Mean	-	0.857	0.711
Standard Deviation	-	0.077	0.19
Lagrange Multiplier Test	-	2405.14	544.10
Hausman Test	-	0.000	0.000
R-squared	-	0.071	0.227

a. See text for a description of alternative model specifications, and Appendix Table A.1 for variable definitions and data sources.

Appendix Table A.7
Frontier Regression Estimates of Total Cost Function with
Efficiency Correlates,[a] Model Specifications A and B, Panel Hospitals, 1982-1993

Model Parameters[b]	MLE Coefficients (Absolute t-ratios) Cost Model B	Cost Model A
β_1	0.2238 (4.70)	0.3576 (4.49)
β_2	0.0056 (0.91)	0.0068 (0.32)
β_3	0.3585 (5.32)	0.5186 (7.47)
β_4	-0.9996 (8.49)	-1.2087 (8.34)
β_5	0.6243 (10.04)	0.6121 (11.50)
β_6	0.1781 (5.45)	0.1427 (4.52)
γ_1	0.4705 (32.72)	-1.5889 (6.13)
γ_2	0.0380 (1.91)	1.7210 (2.81)
γ_3	0.4676 (21.99)	-1.6275 (1.19)
γ_4	-0.0055 (2.71)	-0.0594 (8.50)
γ_5	0.4013 (1.46)	0.0402 (4.44)
γ_6	-	0.0528 (7.31)
β_{11}	-0.0209 (5.74)	0.0236 (4.42)
β_{22}	-0.0007 (0.93)	0.0021 (2.81)
β_{33}	-0.0247 (5.81)	0.0084 (0.58)
β_{44}	0.1683 (4.18)	0.0366 (0.70)
β_{55}	0.0181 (3.48)	0.0206 (2.24)
β_{66}	0.0106 (14.06)	0.0097 (10.69)
γ_{11}	-	0.1005 (7.51)
γ_{22}	-	-0.0946 (3.04)
γ_{33}	-	0.0976 (1.35)
γ_{44}	-	-0.0031 (7.87)
γ_{55}	-	0.0027 (4.63)
γ_{66}	-	0.0031 (4.47)

Appendix Table A.7 (Continued)

Model Parameters[b]	MLE Coefficients (Absolute t-ratios) Cost Model B	Cost Model A
β_{12}	-	-0.0293 (5.67)
β_{13}	-	-0.0924 (3.87)
β_{14}	-	0.0669 (1.78)
β_{15}	-	-0.0441 (2.47)
β_{16}	-	0.0099 (0.90)
β_{23}	-	0.0180 (3.31)
β_{24}	-	0.0087 (0.82)
β_{25}	-	0.0018 (0.42)
β_{26}	-	0.0019 (0.88)
β_{34}	-	0.0067 (1.25)
β_{35}	-	-0.0542 (3.07)
β_{36}	-	-0.0020 (0.23)
β_{45}	-	0.0165 (0.42)
β_{46}	-	-0.0446 (2.18)
β_{56}	-	0.0040 (0.77)
β_{77}	0.1290 (4.43)	-
β_{47}	-0.1482 (7.07)	-
β_{57}	-0.0714 (9.26)	-
β_{67}	-0.0311 (8.00)	-
Control: Religious (=1)	-0.0010 (0.69)	-0.0106 (0.76)
Proprietary Corporation (=1)	-0.0287 3.19)	-0.0349 (3.80)
Other Proprietary (=1)	-0.0116 (0.56)	-0.0061 (0.28)
Government (=1)	-0.0774 (6.45)	-0.0844 (7.37)
Ownership Change (=1)	0.0316 (2.20)	0.0214 (1.41)

Appendix Table A.7 (Continued)

Model Parameters[b]	MLE Coefficients (Absolute t-ratios) Cost Model B	Cost Model A
Beds: 100 or Fewer (=1)	-0.0837	-0.0841
	(5.78)	(5.99)
300 or More (=1)	0.0599	0.0495
	(4.35)	(3.67)
Physician Staff Mix (Index/100)	0.6070	0.6863
	(8.20)	(8.89)
Wage Rates: Above Local Average (=1)	-0.0622	-0.0194
	(6.92)	(2.00)
Below Local Average (=1)	0.0480	0.0074
	(5.62)	(0.81)
Net Annual Investment ($ Millions)	0.0029	0.0028
	(7.56)	(7.29)
Service Mix: Above Local Average (=1)	-0.0086	-0.0107
	(0.64)	(0.88)
Below Local Average (=1)	0.0190	0.0127
	(1.50)	(0.97)
Patient Care Revenue Ratio	-0.4429	-0.5526
	(6.07)	(8.30)
Market Share (Endogenous Percent)	-0.1358	-0.1940
	(6.02)	(8.44)
α_0	2.0157	16.324
	(7.68)	(2.50)
$\sigma u/\sigma v$	1.6686	1.4195
	(20.21)	(16.95)
$\sqrt{\sigma^2 v+\sigma^2 u}$	0.2142	0.1933
	(43.11)	(30.86)
N	2,232	2,232
Log-likelihood	1005.36	1132.38

a. See text equations (6a and 6b) for parameter notation and the text for a discussion of model specification.

b. See Appendix Table A.1 for variable definitions.

Appendix Table A.8
Regression Estimates, Probit Models of Difference in FREG and DEA Efficiency Scores,[a]
Specifications with Output Pattern Variables and Interactions, 1982-1993

Explanatory Variables	Probit Coefficients (Absolute t-ratios)		
	DEA-Adjusted FREG > -0.05 (=1)	DEA-Adjusted FREG > -0.05 (=1)	DEA-Adjusted FREG > -0.05 (=1)
Control: Religious (=1)	-0.5353	-0.5318	-0.5390
	(4.22)	(4.20)	(4.28)
Proprietary Corporation (=1)	0.1999	0.2082	0.2517
	(2.77)	(2.89)	(3.57)
Other Proprietary (=1)	0.1256	0.1247	0.1754
	(0.79)	(0.79)	(1.11)
Government (=1)	0.0382	0.0268	0.0206
	(0.40)	(0.28)	(0.22)
Ownership Change (=1)	0.1668	0.1738	0.1760
	(1.32)	(1.38)	(1.39)
Beds: 100 or Fewer (B_{100} =1)	0.2641	-0.0961	-
	(2.67)	(0.58)	
300 or More (B_{300} =1)	-0.2422	-0.2415	-
	(3.01)	(1.38)	
Inconsistent Output Pattern: ΔQ (=1)	0.2044	0.2847	-
	(2.81)	(0.21)	
$\Delta Q * B_{100}$ (=1)	-	0.5569	0.5176
		(2.99)	(4.84)
$\Delta Q * B_{300}$ (=1)	-	-0.0078	-0.1736
		(0.04)	(2.25)
Physician Staff Mix (Index/100)	-4.4920	-5.0084	-4.9203
	(7.10)	(7.64)	(9.57)
Wage Rates: Above Local Average (=1)	-0.1614	-0.1580	-0.1658
	(2.22)	(2.17)	(2.29)
Below Local Average (=1)	0.0933	0.0961	0.1064
	(1.31)	(1.35)	(1.50)
Net Annual Investment ($ Millions)	-0.0934	-0.0117	-0.0142
	(2.32)	(2.61)	(3.28)
Service Mix: Above Local Average (=1)	0.3383	0.2879	0.1946
	(3.50)	(2.86)	(2.18)
Below Local Average (=1)	-0.1590	-0.1673	-0.1673
	(1.66)	(1.74)	(1.75)
Patient Care Revenue Ratio	0.3765	0.6057	0.5314
	(0.51)	(0.82)	(0.72)
Market Share (Endogenous Percent)	0.0036	0.0193	0.0242
	(0.02)	(0.10)	(0.13)
Constant	0.2393	0.2787	0.2956
	(0.33)	(0.38)	(0.42)
N	2,232	2,232	2,232
Model Chi-Squared	341.24	353.87	347.75

a. See text for a description of alternative model specifications and variable definitions.